PATENT
37 CFR 1.53(b) CONTINUATION-IN-PART

Date: DECEMBER 3, 1998

Docket No.: LYC 5

Assistant Commissioner for Patents
Washington, D.C. 20231

Sir:

This is a Request for filing a x continuation-in-part application under 37 C.F.R. § 1.53(b) of pending prior Application No. 08/627,436 filed on APRIL 4, 1996 ________, the entire contents of which are hereby incorporated by reference, by

ANDREW K. LANG AND DONALD M. KOSAK

for

AN INFORMATION SYSTEM AND METHOD FOR FILTERING A MASSIVE FLOW OF INFORMATION ENTITIES TO MEET USER INFORMATION CLASSIFICATION NEEDS

1. X Enclosed is an application consisting of specification, claims, declaration and drawings/photographs which are a true copy of the prior Application.

2. X The filing fee has been calculated as follows:

			LARGE ENTITY	**SMALL ENTITY**
	BASIC FEE		760.00 ~~$790.00~~	~~$395.00~~
	NUMBER FILED	NUMBER EXTRA	RATE FEE	RATE FEE
TOTAL CLAIMS	16 - 20 =	0	x 18 = 0	
INDEPENDENT CLAIMS	8 - 3 =	5	x 78 = $390	
0 MULTIPLE DEPENDENT CLAIMS PRESENTED			~~+ $270.00~~	~~+ $135.00~~
		TOTAL	$1150	

3. X A check in the amount of $1150.00________ to cover the filing fee and recording fee (if applicable) is enclosed.

4. ___ Please charge Deposit Account No. in the amount of $_______. A triplicate copy of this request is enclosed.

5. X Amend the specification by inserting before the first line thereof the following:

   a. --This application is a X continuation-in-part of copending Application No. 08/627,436 ___, filed on APRIL 4, 1996 _________, the entire contents of which are hereby incorporated by reference.--

   b. --This application is a _____ continuation ____ divisional of copending Application No. ___________ ________, filed on ______________________________. Application No. _________ is the national phase of PCT International Application No. PCT/___/___ filed on ____________________________ under 35 U.S.C. § 371. The entire contents of each of the above identified applications are hereby incorporated by reference.--

6. ___ Transfer the drawings/photographs from the prior application to this application and abandon said prior application as of the filing date accorded this

application. A duplicate copy of this request is enclosed for filing in the prior application file.

7. _X_ Enclosed is/are _10_ sheet(s) of ___ __drawings/photographs.

8. ___ A verified statement claiming small entity status was filed in prior Application No. ___ on ___ ___. See attached copy of verified statement claiming small entity.

9. ___ The prior application is assigned to ___ ___ ___

10. _X_ A Preliminary Amendment is enclosed.

11a. ___ Priority of Application No(s). ___ ___ filed in ___ ___ on ___ ___ is/are claimed under 35 U.S.C. § 119. See attached copy of the Letter claiming priority filed in the prior application on ___.

11b. ___ Priority of International Appln. ___ filed on ___ under the Patent Cooperation Treaty and ___ Application No. ___ filed in ___ on ___ under 35 U.S.C. § 119 are hereby reclaimed.

12. ___ An Information Disclosure Statement and PTO-1449 form(s) are attached hereto for the Examiner's consideration.

13. _X_ Address all future communications to:

Jeffrey M. Snider
General Counsel
Lycos, Inc.
400-2 Totten Pond Road
Waltham, MA 02154

Telephone: (781) 370-2852
Fax: (781) 370-2600

14. ___ An extension of time for ___ month(s) until ___ has been submitted in parent Application No. ___ in order to establish copendency with the present application.

15. X Also to be submitted is the following:

Executed declaration in accordance with 37 CFR 1.63 will follow.

Respectfully submitted,

Edward F. Possessky

By Edward F. Possessky

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Rev. 2/18/98
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PATENT

ATTORNEY DOCKET #: LYC5

DATE: DECEMBER 3, 1998

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re application of: Andrew K. Lang et al

Application #: filed herewith as continuation-in-part application of parent application SN 08/627,436 which was filed on April 4, 1996

Group Art Unit:

Examiner:

For: **COLLABORATIVE/ADAPTIVE SEARCH ENGINE**

Assistant Commissioner for Patents

Washington, DC 20231

PRELIMINARY AMENDMENT

Sir:

Prior to the first Examination, please amend this continuation-in-part application as follows:

IN THE TITLE:

Please amend the title to read as follows: --COLLABORATIVE/ADAPTIVE SEARCH ENGINE--.

IN THE SPECIFICATION:

Please amend the Specification as follows:

Page 1, delete lines 1-5, and insert --COLLABORATIVE/ADAPTIVE SEARCH ENGINE--.

Page 1, delete lines 8- 25.

Page 1, after line 7, insert:

--The present invention relates to information processing systems for large or massive

information networks, such as the internet, and more particularly to such information systems especially adapted for operation in portal and other web sites wherein a search engine operates with collaborative and content-based filtering to provide better search responses to user queries.

In the operation of the internet, a countless number of informons are available for downloading from any of at least thousands of sites for consideration by a user at the user's location. A user typically connects to a portal or other web site having a search capability, and thereafter enters a particular query, i.e., a request for informons relevant to a topic, a field of interest, etc. Thereafter, the search site typically employs a "spider" scanning system and a content-based filter in a search engine to search the internet and find informons which match the query. This process is basically a pre-search process in which matching informons are found, at the time of initiating a search for the user's query, by comparing informons in an "informon data base" to the user's query. In essence, the pre-search process is a short term search for quickly finding and quickly identifying information entities which are content matched to the user's query.

The return list of matching informons can be very extensive according to the subject of the query and the breadth of the query. More specific queries typically result in shorter return lists. In some cases, the search site may also be structured to find web sites which probably have stored informons matching the entered query.

Collaborative data can be made available to assist in informon rating when a user actually downloads an informon, considers and evaluates it, and returns data to the search site as a representation of the value of the considered informon to the user.

In the patent application which is parent to this continuation-in-part application, i.e. Serial Number 08/627,436, filed by the present inventors on April 4, 1996, and hereby incorporated by reference, an advanced collaborative/content-based information filter system is employed to provide superior filtering in the process of finding and rating informons which match a user's query. The information filter structure in this system integrates content-based filtering and collaborative filtering to determine relevancy of informons received from various sites in the internet or other network. In operation, a user enters a query and a corresponding "wire" is established, i.e., the query is profiled in storage on a content basis and adaptively updated over time, and informons obtained from the network are compared to the profile for relevancy and

ranking. A continuously operating "spider" scans the network to find informons which are received and processed to determine relevancy to the individual user's wire or to wires established by numerous other users.

The integrated filter system compares received informons to the individual user's query profile data, combined with collaborative data, and ranks, in order of value, informons found to be relevant. The system maintains the ranked informons in a stored list from which the individual user can select any listed informon for consideration.

As the system continues to feed the individual user's "wire", the stored relevant informon list typically changes due to factors including a return of new and more relevant informons, adjustments in the user's query, feedback evaluations by the user for considered informons, and updatings in collaborative feedback data. Received informons are similarly processed for other users' wires established in the information filter system. Thus, the integrated information filter system performs continued long-term searching, i.e., it compares network informons to multiple users' queries to find matching informons for various users' wires over the course of time, whereas conventional search engines initiate a search in response to an individual user's query and use content-based filtering to compare the query to accessed network informons typically to find matching informons during a limited, short-term search time period.

The present invention is directed to an information processing system especially adapted for use at internet portal or other web sites to make network searches for information entities relevant to user queries, with collaborative feedback data and content-based data and adaptive filter structuring, being used in filtering operations to produce significantly improved search results.--

Delete pages 2-9.

Page 10, delete lines 1-8 and lines 11-29.

Page 10, after line 10, insert:

-- A search engine system employs a content-based filtering system for receiving informons from a network on a continuing basis and for filtering the informons for relevancy to a wire or demand query from an individual user. A feedback system provides feedback data from other users.

Another system controls the operation of the filtering system to filter for one of a wire response and a demand response and to return the one response to the user. The filtering system combines pertaining feedback data from the feedback system with content profile data in determining the relevancy of the informons for inclusion in at least a wire response to the query.--

Delete pages 11-14.

Page 15, delete lines 1-18.

Page 16, after line 15, insert --Figure 8 is a logic diagram illustrating a search selection feature of the invention;

Figure 9 is a functional block diagram of an embodiment of the invention in which an integrated information processing system employs a search engine and operates with combined collaborative filtering and content-based filtering, which is preferably adaptive, to develop responses to user queries.

Figure 10 shows another and presently preferred embodiment of the invention in which an information processing system includes an integrated filter structure providing collaborative/adaptive-content-based filtering to develop longer term, continuing responses to user queries, and a search engine structure which provides short term, demand responses to user queries, with the system directing user queries to the appropriate structure for responses.--

Page 16, line 18 delete "provides", and insert --is preferably configured with--.

Page 16, line 23, delete "invention", and insert --information filtering is long term in the sense that it operates on a continuing basis, and--.

Page 17, line 1, delete "invention", and insert --filter--.

Page 17, line 6, after "method.", delete the rest of the line.

Page 17, delete lines 7 and 8.

Page 17, line 16, delete ", for example,".

Page 20, line 4, delete "invention employs", and insert --system apparatus includes a filter structure having--, and delete "content", and insert --content-based--.

Page 20, line 7, before "The", insert --As used herein, the term "content-based filter" means a filter in which content data, such as key words, is used in performing the filtering process. In a collaborative filter, other user data is used in performing the filtering process. A collaborative

filter is also sometimes referred to as a "content" filter since it ultimately performs the task of finding an object or document having content relevant to the content desired by a user. If there are some instances herein where the term "content filter" is used as distinguished from a collaborative filter, it is intended that the term "content filter" mean "content-based filter."--.

Page 20, line 24, delete "invention", and insert --filter structure--.

Page 21, line 5, delete "can be provided".

Page 21, line 7, delete "profile", and insert --profiles--.

Page 21, line 12, after "author", insert --,--.

Page 21, line 18, delete "memclient is view", and insert --new member client is viewed--"

Page 23, line 11, delete "fora for".

Page 23, line 12, delete "obtaining".

Page 24, line 6, delete "of the invention".

Page 24, line 7, delete "the".

Page 24, line 12, delete "invention", and insert --filter structure--.

Page 24, line 12, delete ", and".

Page 24, line 13, delete "tracking shifts in,".

Page 24, line 15, before "whether", insert --and tracking shifts in the preferences--.

Page 24, line 17, delete "This" and insert --The--.

Page 25, delete lines 17-25.

Delete pages 26-32.

Page 33, delete lines 1-6.

Page 33, line 8, after "apparatus 1", insert --structured--, and delete "according to the invention herein", and insert --for search engine implementation in accordance with the invention as described subsequently herein in connection with Figures 8 and 9--.

Page 33, line 11, delete "recognized", and insert --recognize--.

Page 34, line 4, delete "have an informon", and insert --has an information--.

Page 34, line 5, delete "the", and insert --an--.

Page 34, line 5, delete "the", and insert --an--.

Page 34, line 7, after "of", insert --raw--.

Page 34, line 15, delete “the”(every occurrence), and insert --a--.

Page 34, line 21, delete “bases”, and insert --based--.

Page 35, line 7, delete “35".

Page 35, line 12, delete “an”, and insert --a--.

Page 35, line 22, delete “technique”, and insert --techniques--.

Page 36, line 11, delete “conyent”, and insert --content--.

Page 36, line 22, delete “The”, and insert --A--.

Page 38, line 4, insert “(melding of agent “minds”)” after --domains--.

Page 38, line 8, delete “collaborative”, and insert --content--.

Page 38, line 16, delete “processor”(both occurrences), and insert --processors--.

Page 38, line 22, delete “processor”, and insert --processors--.

Page 40, line 11, delete “processor”, and insert --processors--.

Page 40, line 12, delete “processor”, and insert --processors--.

Page 40, line 13, delete “processor”, and insert --processors--.

Page 40, line 17, delete “processor”, and insert --processors--.

Page 40, line 19, delete “processor”, and insert --processors--.

Page 40, line 20, delete “community”, and insert --communities--, and delete “a”.

Page 40, line 21, delete “profile”, and insert --profiles--, delete “is”, and insert --are--, and delete “each of”.

Page 40, line 25, delete “processor”, and insert --processors--.

Page 41, line 4, delete “profiling”, and insert --filtering--.

Page 41, line 6, delete “processor”, and insert --processors--.

Page 41, line 7, delete “processor”, and insert --processors--.

Page 41, line 17, delete “profiles”.

Page 41, line 19, delete “profiles”.

Page 41, line 22, delete “responsive to the member client feedback”.

Page 41, line 23, delete “profiles 65a-d”.

Page 42, line 8, delete “respective”.

Page 42, line13, delete “Apparatus 50 also”, and insert --Any of the adaptive filters 66a-d--, and

delete “as one or”.

Page 42, line 14, delete “more of adaptive filter 66a-d”.

Page 42, line 20, before “apparatus”, insert --the--, and after “apparatus”, insert --50--.

Page 42, after “additional”, insert --respective--.

Page 43, line 14, delete “ The invention herein also comprehends a method”, and insert --The above described system operates in accordance with--.

Page 44, line 6, before “distributed”, insert --machine--.

Page 44, line 7, delete “step”, and insert --substep--, and delete “producing”, and insert --using--.

Page 44, line 8, delete “step”, and insert --substep--.

Page 44, line 9, delete “producing”, and insert --using--.

Page 44, line 10, delete “at steps”, and insert --in substeps--.

Page 44, line 13, delete “of”.

Page 44, line 18, delete “includes”, and insert --include--.

Page 44, line 23, after “the”, insert --user--.

Page 44, line 25, before “feedback”, insert--user--.

Page 45, line 8, delete “describes”, and insert --illustrates--, and delete “embodiment of”.

Page 45, line 9, delete “, according to the invention herein”.

Page 45, line 13, delete “a”.

Page 45, line 23, delete “the”, and insert --a--.

Page 46, line 18, delete “respective”, and insert --pertaining--.

Page 46, line 22, delete “employs”, and insert --employ--.

Page 47, delete lines 6-7, and insert --The information filtering method shown in Figure 5--.

Page 47, line 8, delete “invention”.

Page 47, line 17, delete “profiling”, and insert --filtering--.

Page 47, line 23, delete “In the present invention, it”, and insert --It--.

Page 48, line 13, delete “that”.

Page 48, line 14, delete “can be”.

Page 48, line 15, delete “assumed”.

Page 48, line 19, delete “are”, and insert --be--.

Page 53, line 8, delete "exceed", and insert --exceeded--.

Page 53, line 18, delete "an".

Page 57, line 16, delete "An exemplary of", and insert --As an example--.

Page 57, line 23, after "TABLE 1", insert --(following the text of this specification)--.

Page 58, line 27, delete "130", and insert --430--.

Page 59, delete line 10 through the last line.

Delete pages 60-62.

Page 68, line 7, after "However,", insert --the invention can be embodied with use of--.

Page 68, line 8, delete "as was used earlier in the discussion of", and insert --like that previously considered in connection with--.

Page 68, line 10, delete "is preferred to be able to include", and insert --preferably includes--.

Page 69, line 14, delete "a".

Page 72, line 17, after "used", insert --to--.

Page 72, line 22, delete "one', and insert --a preferred--.

Page 72, line 23, delete "heirarchy", and insert --system--.

Page 73, line 5, delete "as", and insert --As--.

Page 73, line 8, delete "Mindpools", and insert --Sub-mindpools--.

Page 73, line 9, delete "mindpools", first appearance, and insert --sub-sub-mindpools--.

Page 73, line 10, delete "502a-3. Mindpools", and insert --503a-c. Sub-sub-mindpools--.

Page 74, line 18, after "communication", insert --be provided--.

Page 75, line 25, after "down", insert --the--.

Page 75, line 14, delete "computer-", and insert --computer-guided--.

Page 75, line 19, delete "because".

Page 77, line 25, delete "is", and insert --be--.

Page 78, line 19, delete "An example of", and insert --The following exemplifies--.

Page 78, line 20, delete "is given presently.", and insert --:--.

Page 82, after line 10, beginning with a new paragraph, insert:

--The invention of this continuation-in-part application, as shown in Figures 8 and 9, provides a collaborative and preferably adaptive search engine system in which elements of the

structure and principles of operation of the apparatus of Figures 1-7 are applied. Accordingly, a search engine system of the invention, as preferably embodied, integrates collaborative filtering with adaptive content-based filtering to provide improved search engine performance. The acronym "CASE" refers to a search engine system of the invention, i.e., a collaborative, adaptive search engine.

In the operation of conventional search engines at portal web sites, user queries are searched on demand to find relevant informons across the web. Content-based filtering is typically used in measuring the relevacy of informons, and the search results are resented in the form of a list of informons ranked by relevancy.

The present invention combines collaborative filtering with content-based filtering in measuring informons for relevancy, and further preferably applies adaptive updating of the content-based filtering operation. In providing these results, the invention can be embodied as a search engine system in accordance with different basic structures. In the presently preferred basic structure, an integrated collaborative/content-based filter (Figures 1-7) is operated to provide ongoing or continuous searching for selected user queries, with a "wire" being established for each query. On the other hand, a regular search engine is operated to make immediate or short-term "demand" searches for other user queries on the basis of content-based filtering. This basic structure of the invention is especially beneficial for use in applying the invention to existing search engine structure.

Demand search results can be returned if no wire exists for an input query. Otherwise, wire search results are returned if a wire does exist, or collaborative ranking data can be applied from the wire filter structure to improve the results of the demand search from the regular search engine.

In the currently preferred embodiment, wires are created for the most common queries received by the search engine system. A suitable analysis is applied to the search engine operations to determine which queries are most common, and respective wires are then created for each of these queries. An analysis update can be made from time to time to make wire additions or deletions as warranted.

When a user makes a query for which a wire already exists, wire search results are

preferably returned instead of regular search engine results. As shown in the logic diagram of Figure 7, a user provides a query as indicated by block 20C. The query is applied to a Lookup Table, as indicated by block 22C, block 24C applies a test to determine from the table whether a wire already exists for the new query. If so, block 26C returns results from the existing wire. Otherwise, block 28C commands a demand search by a regular query engine.

With the use of wire search returns, each user can review the returned results and provide feedback data about reviewed documents. Such feedback data is incorporated in the filter profiles used in processing informons for the wire. Therefore, when a future user makes substantially the same query, the wire will have been improved by the incorporation of previous users' feedback data. By analyzing documents which users rate as meeting a particular quality such as interestingness, the system can find common document features which can be used to return more like documents to future users who make substantially the same query.

Alternatively, all queries applied to a search engine system of the invention can set up new wires. After a search query is presented to the search engine system, a wire is created on the basis of the query terms, and all new documents subsequently received from the network are filtered by the new wire. A push-model may be used to send all passed, new documents to the user.

Among other basic search engine system structures, an integrated system can be employed in which collaborative and content-based filtering is structured to provide demand searches with or without collaborative filtering, or wire searches. In the operation of the preferred basic structure and other basic structures, a query processor can be employed, if needed, to make search-type assignments for user queries. Generally, basic search engine system structures of the invention are preferably embodied with the use of a programmed computer system.

Collaborative filtering employs additional data from other users to improve search results for an individual user for whom a search is being conducted. The collaborative data can be feedback informon rating data, and/or it can be content-profile data for agent mind melding which is more fully disclosed in Serial Number (Docket # LYC 4), entitled INTEGRATED COLLABORATIVE/CONTENT-BASED FILTER STRUCTURE EMPLOYING SELECTIVELY SHARED, CONTENT-BASED PROFILE DATA TO EVALUATE

INFORMATION ENTITIES INA MASSIVE INFORMATION NETWORK, filed by the current inventors on November 19, 1998, and hereby incorporated by reference.

Many types of user rating information can be used. For example, users can sort documents which they have read from best to worst. Alternatively, users can select on a scale (numeric, such as 1 to 10, or worded, such as good, medium, poor) how much they enjoyed reading a document. Further, user monitoring can measure time spent by users on each document, thereby indicating user interest (normalized by document length). Among other possibilities, the choices of documents for reading by other users can be simply used as an indiction of interesting documents. In all cases, the feedback rating data can be based on interestingness or any of a variety of other document qualities, as described in connection with Figures 1-7.

Feedback ranking information can be used in a number of ways, and the invention is not limited by the method of feedback information use. Use methods range in spectrum from weighting relative ranks by a set amount (possibly equally, possibly heavy weighting one above the other) to dynamically adjusting the weight by measuring how statistically significant the user feedback is. For example, if only one person has ranked an article, it may not be significant. However, if many people have consistently ranked an article the same, more credibility may be placed on the user's weighting.

Figure 9 shows a generalized embodiment of the invention in which system elements in a CASE system 30C are integrally configured to provide wire and/or demand searches. A query processor 32C receives queries from an individual user 34C and other users 36C. A mode selector 38C responds to the currently processed query to set a content-based filter structure 40C for wire search operation or demand search operation. In the preferred appication of the invention, the wire mode is selected only if a wire already exists, and wires exist only for those queries found to be commonly entered as previously described. In the demand search mode, the filter structure 40C can function similarly to a normal search engine.

Otherwise, various schemes can be used for determining whether a wire search or a demand search is made. For example, every query can call for a wire search, with a demand search being made the first time a particular query is entered and with wire searches being made

for subsequent entries of the same query. As another example, the user may select a demand search, or, if continuing network searching is desired, the user may select a wire search.

The filter structure 40C operates in its set wire search mode or demand search mode, and employs content-based profiles 42C in content-based filtering (preferably multi-level as described in connection with Figures 1-7). Wire profiles 42C1 are adaptively updated with informon-evaluation, feedback data from users respectively associated therewith. These profiles are used by the filter structure 40C in wire searches in the wire mode.

Demand profiles 42C2 are used by the filter structure 40C in demand searches in the demand mode. Collaborative profile data can be integrated with the wire profiles through agent mind melding 43C as previously explained.

A spider system 46C scans a network 44C to find informons for a current demand search , and to find informons with continued network scanning for existing wires. In selecting available informons for return, the spider system 46C uses a content threshold derived from the content-based profile for which an informon search is being conducted.

In many instances, it s preferable that the spider system 46C have a memory system 46CM which holds an informon data base wherein index information is stored from informons previously collected from the network. In this manner, demand searches can be quickly made from the spider memory 46CM as opposed to making a time consuming search and downloading in response to a search demand query from the search engine.

A search return processor 48C receives either demand search informons or wire search informons passed by the content-based filter structure 40C according to the operating mode of the latter, and includes an informon rating system which is like that of Figure 6. The informon rating system combines content-based filtering data with collaborative feedback rating data, from users through a feedback processor 50C at least in the wire search mode and, if desired, in the demand search mode.

In the wire search mode, the processor 48C rates informons on a continuing basis as they are received from the network 44C through the spider system 46C as indicated by the reference character 48C1. In the demand search mode, the processor 48C rates informons returned by the spider system 46C in a demand search as indicated by the reference character 48C2.

Collaborative rating data is used in the informon rating process in the wire search mode, and if applied in the demand search mode, to the extent that collaborative data is available for the informons in the search return. Search results are returned to the users 34C and 36C from the search return processor 48C as shown in Figure 9.

The invention is preferably embodied as shown in Figure 10. A query processor 60C receives queries from an individual user 62C and other users 64C and determines whether a wire already exists for each entered query. If a wire exists, the query is routed to a collaborative/content-based filter structure 66C like that of Figures 1-7. A spider system 68C continuously scans a network 70C for informons providing a threshold-level match for content based profiles (i.e., preprocessing profiles at the top level of the preferred multi-level filter structure, at least one of which reflects the content profile of a current wire query). Informons which are passed by the filter 66C for existing wires are stored in a memory 72C according to the wire or wires to which they belong.

A feedback processor 74C is structured like the mindpool system of Figure 7 to provide collaborative feedback data for integration with the content-based data in the measurement of informon relevancy by the filter 66C. An informon rating structure like that of Figure 6 is employed for this purpose. Adaptive feedback data is applied from the users to the filter 66C as shown in order to update content profiles as previously described.

If no wire exists for a currently input query, the query is sent to a regular search engine where a content profile is established for content based filtering of informons returned by a spider system 78C in a demand search of the network 70C. The spider system 78C can have its own memory system 78CM as considered in connection with the spider 46C of Figure 9.

Once filtering is performed on returned informons, those informons which provide a satisfactory match to the query are returned as a list to the user through a search return processor 80C. The processor 80C creates a new wire for the current query for which a demand search was made, if a demand search memory 82C indicates that the current query has been made over time with sufficient frequency to qualify as a "common" query for which a wire is justified. As indicated by dashed connector line 80FD, collaborative feedback data can be, and preferably is, integrated into the demand search processing by the processor 80C.--

Page 82, delete lines 11-16.

Page 82, line 17, delete "Furthermore, many", and insert --Many--.

Delete pages 86-90.

IN THE CLAIMS:

Please cancel claims 1-84.

Please add the following claims:

85. A search engine system comprising:

a first system for receiving informons from a network on a continuing search basis, for filtering such informons for relevancy to a query from an individual user, and for storing a ranked list of relevant informons as a wire;

a second system for receiving informons from a network on a current demand search basis and for filtering such informons for relevancy to the query from the individual user; and

a third system for selecting at least one of the first and second systems to make a search for the query and to return the wire or demand search results to the individual user.

86. The system of claim 85 wherein the third system selects the first system to make a wire search only if a wire already exists for the query.

87. The system of claim 85 wherein:

a feedback system is provided for receiving collaborative feedback data from system users relative to informons considered by such users; and

at least the first system combines pertaining data from the feedback system with content profile data of the first system in filtering each informon for relevance to the query and inclusion in the wire.

88. The system of claim 87 wherein the first system includes a multi-level, content-based filter having descending levels including at least an upper preprocessing level, a middle user community level, and a bottom user level.

89. The system of claim 85 wherein adaptive user feedback data is applied at least to the first system to provide updating of content profile data employed therein.

90. A search engine system comprising:

a system for scanning a network to make a demand search for informons relevant to a

query from an individual user;

a content-based filter system for receiving the informons from the scanning system and for filtering the informons on the basis of applicable content profile data for relevance to the query; and

a feedback system for receiving collaborative feedback data from system users relative to informons considered by such users;

the filter system combining pertaining feedback data from the feedback system with the content profile data in filtering each informon for relevance to the query.

91. The system of claim 90 wherein adaptive user feedback data is applied to the content-based filter to provide a learning component for content profile data employed therein.

92. The system of claim 90 wherein:

the scanning system further scans the network on a continuing basis to make a wire search for informons relevant to wire queries from system users; and

the filter system combines pertaining feedback data from the feedback system with applicable content profile data in filtering each wire informon for relevance to applicable wire query.

93. A search engine system comprising:

a content-based filtering system for receiving informons from a network on a continuing basis and for filtering the informons for relevancy to a wire or demand query from an individual user;

a feedback system providing feedback data from other users;

a system for controlling the operation of the filtering system to filter for one of a wire response and a demand response and to return the one response to the user; and

the filtering system combining pertaining feedback data from the feedback system with content profile data in determining the relevancy of the informons for inclusion in at least a wire response to the query.

94. The system of claim 93 wherein:

the content-based filtering system includes a collaborative/content based filter for filtering informons for relevancy to a wire query on a continuing basis; and

the content-based filtering system includes a regular search engine for filtering informons for relevancy to a demand query.

95. The system of claim 94 wherein adaptive user feedback data is applied at least to the collaborative/content-based filter to provide learning for content profile data employed therein.

96. A method for operating a search engine system comprising:

receiving informons in a first system from a network on a continuing search basis, for filtering such informons for relevancy to a query from an individual user and for storing a ranked list of relevant informons as a wire;

receiving informons in a second system from a network on a current demand search basis for filtering such informons for relevancy to the query from the individual user; and

selecting at least one of the first and second systems to make a search for the query and to return the wire or demand search results to the individual user.

97. A method for operating a search engine system comprising:

scanning a network to make a demand search for informons relevant to a query from an individual user;

receiving the informons in a content-based filter system from the scanning system and filtering the informons on the basis of applicable content profile data for relevance to the query;

receiving collaborative feedback data from system users relative to informons considered by such users; and

combining pertaining feedback data with the content profile data in filtering each informon for relevance to the query.

98. A method for operating a search engine system comprising:

receiving informons in a content-based filtering system from a network on a continuing basis and filtering the informons for relevancy to a wire or demand query from an individual user;

providing feedback data from other users;

controlling the operation of the filtering system to filter for one of a wire response and a demand response and to return the one response to the user; and

combining pertaining feedback data with content profile data in the filtering system in

determining the relevancy of the informons for inclusion in at least a wire response to the query.

99. A search engine system comprising:

means for receiving informons from a network on a continuing search basis, for filtering such informons for relevancy to a query from an individual user, and for storing a ranked list of relevant informons as a wire;

means for receiving informons from a network on a current demand search basis and for filtering such informons for relevancy to the query from the individual user; and

means for selecting at least one of the first and second systems to make a search for the query and to return the wire or demand search results to the individual user.

100. A search engine system comprising:

means for content-based filtering informons received from a network on a continuing basis for relevancy to a wire or demand query from an individual user;

means for collecting feedback data from other users;

means for controlling the operation of the filtering means to filter for one of a wire response and a demand response and to return the one response to the user; and

the filtering means combining pertaining feedback data from the feedback system with content profile data in determining the relevancy of the informons for inclusion in at least a wire response to the query.

IN THE ABSTRACT:

Replace the Abstract of the identified parent application with the Abstract on the next page.

ABSTRACT OF THE DISCLOSURE

A search engine system is provided for a portal site on the internet. The search engine system employs a regular search engine to make one-shot or demand searches for information entities which provide at least threshold matches to user queries. The search engine system also employs a collaborative/content-based filter to make continuing searches for information entities which match existing wire queries and are ranked and stored over time in user-accessible, system wires corresponding to the respective queries. A user feedback system provides collaborative feedback data for integration with content profile data in the operation of the collaborative/content-based filter. A query processor determines whether a demand search or a wire search is made for an input query.

REMARKS

This Preliminary Amendment is being submitted to amend the specification formally in line with amendments made to the specification in the parent to this continuation-in-part application and to add claims to the invention of this application, i.e., claims based on subject matter disclosed in this application along with subject matter disclosed in the parent application. In addition, formal amendments have been made to the specification to align the text to a reasonable degree to the scope of the invention subject matter of this continuation-in-part application. This subject matter relates to integrated collaborative and content-based filtering in search engine systems preferably providing both demand searches and continuing or wire searches for user queries.

The current invention is directed to improving the performance of search engines, such as those used at portal sites of the internet. The invention achieves performance improvement through the application of collaborative feedback data to provide integrated collaborative/content-based filtering in search engine operations. The invention further achieves performance improvement through the provision of a filter system which selectively provides demand searches or continuing (wire) searches for user queries. Added text on page 82 provides more detail on the scope, structure and operation of the invention. As indicated, the structure and operation of embodiments can be varied considerably within the spirit and scope of the principles of the invention.

Claims 85-100 vary in scope in defining the invention over the known prior art. These claims define, in apparatus, method and means formats, various invention features considered in the above description and disclosed in the specification and drawings, as amended. Accordingly, the Examiner should allow these claims and pass this application for issue.

If the Examiner has any inquiries or needs to discuss any matter related to this case, the undersigned attorney can be reached by phone at either 703 205 8081 or 703 271 9295 or the assignee's General Counsel Jeffrey Snider can be reached by phone at 781 370 2852.

Respectfully submitted,

Dated: December 3, 1998

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D2306-00002

TITLE

AN INFORMATION FILTER IN A COMPUTER SYSTEM AND A METHOD THEREFOR

BACKGROUND OF THE INVENTION

1. Field of the Invention

This invention relates to an apparatus, method, and computer program product for information filtering, in a computer system receiving a data stream from a computer network.

2. Description of the Relevant Art

Recent developments in computer networking, particularly with regard to global computer internetworking, offer vast amounts of stored and dynamic information to interested users. Indeed, some estimate that hundreds of thousands of news articles stream through the global internetwork each day, and that the total number of files transferred through the global internetwork (hereinafter "network") is in the millions. As computer technology evolves, and as more users participate in this form of communication, the amount of information available on the network will be staggering.

Although databases are relatively static and can be searched using conventional network search engines, current information filtering schemes are ill-suited to thoroughly search the massive, dynamic stream of new information passing through the network each day.

Presently, the information is organized, if at all, to the extent that only skilled, persistent, and lucky, researchers can ferret out meaningful information. Nevertheless, significant amounts of information may go unnoticed. For example, because most existing information filtering schemes focus on locating textual articles, information in other forms -- visual, audio, multimedia, and patterned data -- may be overlooked completely. From the perspective of some users, a few items of meaningful "information" can be obscured by the volume of irrelevant data streaming through the network. Often, the information obtained is inconsistent over a community of like-minded researchers because of the nearly-infinite individual differences in conceptualization and vocabulary within the community. These inconsistencies exist with both the content of the information and the manner in which a search for the content is performed. Furthermore, the credibility of the author, the accuracy, and quality of a given article's content, and thus the article's "usefulness," often are questionable.

The problem of information overload can be more acute for persons involved in multidisciplinary endeavors, e.g., medicine, law, and marketing, who are charged with monitoring developments in diverse professional domains. There are many reasons why users want to communicate with each other about specific things as they find networked resources. However, drawing attention to articles of common interest to a community of researchers, or workgroup, often requires a separate intervention, such as a telephone call, electronic mail, and the like.

Often, membership in a workgroup or community is sharply defined, and workers in one physical community may be unaware of interesting developments in other workgroups or communities, whether or not the communities are similar. This isolation may be at the expense of serendipitous discoveries that can arise from parallel developments in unrelated or marginally-related fields.

Adding to the complexity of the information filtering problem is that an individual user's interests may shift over time, as may those of a community, and many existing information filtering schemes are unable to accept shifts in the individual's interest, the community's interest, or both. Furthermore, information flow usually is uni-directional to the user, and little characterization of secondary user, or group, interests, e.g., the consumer

preferences of users primarily interested in molecular biology or oenology, is derived and used to provide targeted marketing to those users/consumers, and to follow changing demographic trends.

Typically, identifying new information is effected by monitoring all articles in a data stream, selecting those articles having a specific topic, and searching through all of the selected articles, perhaps thousands, each day. One example is where users interact with a web browser to retrieve documents from various document servers on the network. Given the increasing impracticality of this brute-force approach, the heterogenous nature of "information" on the global internetwork, and the growing complexity of social interactions that are evolving concurrently with networking technology, there have been several attempts to address some of the foregoing problems by using adaptive information filtering systems.

In one approach, the information filtering is geared toward content-based filtering. Here, the information filtering system examines the user's patterns of keywords, and semantic and contextual information, to map information to a user's interests. This approach does not provide a mechanism for collaborative activities within a group.

Another approach uses intelligent software agents to learn a user's behavior, i.e., "watching over the shoulder,"

regarding certain types of textual information, for example, electronic mail messages. In this scheme, the agents offer to take action, e.g., delete the message, forward it, etc., on the basis of the user's prior responses to the content of that certain information. Also, this scheme provides a minor degree of inter-agent collaboration by allowing one agent to draw upon the experience of other agents, typically for the purpose of initialization. However, each agent is constrained to develop its expertise in a particular domain within the limited range of the type of information. Also, the passive feedback nature of the "over-the-shoulder" approach can place an unacceptable burden on the system's learner, reducing information throughput and the decreasing the efficiency and usefulness of the overall system. Also, systematic errors can be introduced into the passive feedback error, and the actual response of the user may be misinterpreted.

Another approach uses content-based filtering to select documents for a user to read, and supports inter-user collaboration by permitting the users in a defined group to annotate the selected documents. Annotations tend to take as many forms as there are users, placing the emphasis on characterizing, maintaining, and manipulating a group of diverse annotations, or "meta-documents," from different users in conjunction with the original document.

Collaboration is achieved by enabling the filters of other users to access the annotations. While this approach is useful to the extent that other users can receive a deeper understanding of the comments and criticism provided by a particular user, the costs include the additional computer effort required to implement such collaboration over large, diverse groups and, more importantly, the extra time required for each user to review the comments and criticism of the annotations of the others. Also, annotation sharing and filtering are hampered by the variety in vocabulary and conceptualization among users.

Yet another approach employs collaborative filters to help users make choices based on the opinions of other users. The method employs rating servers to gather and disseminate ratings. A rating server predicts a score, or rating, based on the heuristic that people who agreed in the past will probably agree again. This system is typically limited to the homogenous stream of text-based news articles, does little content-filtering, and can not accommodate heterogenous information.

Other projects have explored individual features such as market-trading optimization techniques for prioritizing incoming messages; rule-based agents for recognize user's usage patterns and suggest new filtering patterns to the user; and personal-adaptive recommendation systems using

exit-questions for rating documents and creating shared recommendations; and the like. In each case, the collaborative and content-based aspects of information filtering are not integrated, and the filters are not equipped to deal with heterogenous data streams.

Many information filtering systems use a weighted average technique for user information feedback that, for example, extracts all of the ratings for an article and takes a simple weighted average over all of the ratings to predict whether an article is relevant to a particular user. Simple weighted averaging, however, tends to destroy the information content contained in the ratings, unless a relatively sophisticated approach is used for the functions generating the simple weighted averages. Little impact is given to factors such as credibility, personal preferences, and the like, which factors tend to be irreversibly blurred during the averaging process. Simple weighted averages, then, can be lacking when one desires to develop information filters that are well-fitted to a particular community and the specific interests of a user unless innovative methods are employed to preserve at least some of the relevant information.

What is need then is an apparatus and method for information filtering in a computer system receiving a data stream from a computer network in which entities of

information relevant to the user, or "informons," are extracted from the data stream using content-based and collaborative filtering. Such a system would employ an adaptive content filter and an adaptive collaborative filter which are integrated to the extent that an individual user can be a unique member client of multiple communities with each community including multiple member clients sharing similar interests.

The system also would implement adaptive credibility filtering, providing member clients with a measure of informon credibility, as judged by other member clients in the community. The system also may implement recommendation filtering and consultation filtering. Furthermore, the system would be preferred to be self-optimizing in that the adaptive filters used in the system would seek optimal values for the function intended by the filter, e.g., collaboration, content analysis, credibility, etc.

3. Citation of Relevant Publications

In the context of the foregoing description of the relevant art, and of the description of the present invention which follows, the following publications can be considered to be relevant:

Susan Dumais, et al. Using Latent Semantic Analysis to Improve Access to Textual Information. In *Proceedings of CHI-88 Conference on Human Factors in Computing Systems.* (1988, New York: ACM)

David Evans et al. A Summary of the CLARIT Project. Technical Report, Laboratory for Computational Linguistics, Carnegie-Mellon University, September 1991.

G. Fischer and C. Stevens. Information Access in Complex, Poorly Structured Information Spaces. In *Proceedings of CHI-91 Conference on Human Factors in Computing Systems.* (1991: ACM)

D. Goldberg, et al. Using Collaborative Filtering to Weave an Information Tapestry. *Communications of the ACM*, 35, 12 (1992), pp. 61-70.

Simon Haykin. *Adaptive Filter Theory.* Prentice-Hall, Englewood Cliffs, NJ (1986), pp. 100-380.

Simon Haykin. *Neural Networks: A Comprehensive Foundation.* Macmillan College Publishing Co., New York (1994), pp. 18-589.

Yezdi Lashkari, et al. Collaborative Interface Agents. In *Conference of the American Association for Artificial Intelligence.* Seattle, WA, August 1994.

Paul Resnick, et al. GroupLens: An Open Architecture for Collaborative Filtering of Netnews. In *Proceeding of ACM 1994 Conference on Computer Supported Cooperative Work.* (1994: ACM), pp. 175-186.

Anil Rewari, et al. AI Research and Applications In Digital's Service Organization. *AI Magazine*: 68-69 (1992).

J. Rissanen. Modelling by Shortest Data Description, *Automatica*, 14:465-471 (1978).

Gerard Salton. Developments in Automatic Text Retrieval. *Science*, 253:974-980, August 1991.

C. E. Shannon. A Mathematical Theory of Communication. *Bell Sys. Tech. Journal*, 27:379-423 (1948).

Beerud Sheth. A Learning Approach to Personalized Information Filtering, Master's Thesis, Massachusetts Institute of Technology, February, 1994.

F. Mosteller, et al. *Applied Bayesian and Classical Inference: The Case of the Federalist Papers. Springer-Verlag*, New York (1984), pp. 65-66.

T.W. Yan et al. Index Structures for Selective Dissemination of Information. Technical Report STAN-CS-92-1454, Stanford University (1992).

Yiming Yang. An Example-Based Mapping Method for Text Categorization and Retrieval. *ACM Transactions on Information Systems*. Vol. 12, No. 3, July 1994, pp. 252-277.

SUMMARY OF THE INVENTION

The invention herein provides a method for information filtering in a computer system receiving a data stream from a computer network. Embedded in the data stream are raw informons, with at least one of the raw informons being of interest to the user. The user is a member client of a community. The method includes the steps of providing a dynamic informon characterization having a plurality of profiles encoded therein, the plurality of profiles including an adaptive content profile and an adaptive collaboration profile; adaptively filtering the raw informons responsive to the dynamic informon characterization, producing a proposed informon thereby; presenting the proposed informon to the user; receiving a feedback profile from the user, responsive to the proposed informon; adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the feedback profile; and updating the dynamic informon characterization responsive to the previous step of adapting. The method is an interactive, distributed,

adaptive filtering method which includes community filtering and client filtering. This filtering respectively produces a community profile and a member client profile. Each of the community filtering and client filtering can be responsive to the adaptive content profile and the adaptive collaboration profile. Furthermore, the dynamic informon characterization is adapted in response to the community profile, the member client profile, or both. The dynamic informon characterization includes a prefiltering profile, an adaptive broker filtering profile, and a member client profile. Also, adaptively filtering includes the steps of prefiltering the data stream according to the prefiltering profile, thereby extracting a plurality of raw informons from the data stream, the prefiltering profile being responsive to the adaptive content profile; filtering the raw informons according to the adaptive broker profile, the adaptive broker profile including the adaptive collaborative profile and the adaptive content profile; and client user filtering the raw informons according to an adaptive member client profile, thereby extracting the proposed informon.

Another embodiment of the method provides the steps of partitioning each user into a plurality of member clients, each member client having a unique member client profile, each profile having a plurality of client attributes; grouping member clients to form a plurality of communities,

each community including selected clients of the plurality of member clients, selected client attributes of the selected clients being comparable to others of the selected clients thereby providing each community with a community profile having common client attributes; predicting at least one community profile for each community using first prediction criteria; predicting at least one member client profile for the client in a community using second prediction criteria; extracting the raw informons from the data stream, each of the raw informons having an informon content; selecting proposed informons from the raw informons, the proposed informons being correlated with at least one of the common client attributes and the member client attributes; providing the proposed informons to the user; receiving user feedback in response to the proposed informons; and updating at least one of the first and second prediction criteria responsive to the user feedback. The method also can include the step of prefiltering the data stream using the predicted community profile, with the predicted community profile identifying the raw informons in the data stream.

In addition, the step of selecting can include filtering the raw informons using an adaptive content filter responsive to the informon content; filtering the raw informons using an adaptive collaboration filter responsive

to the common client attributes for the respective community; and filtering the raw informons using an adaptive member client filter responsive to the unique member client profile.

The method also can include one or more of the steps of credibility filtering, recommendation filtering, and consultation filtering the raw informon responsive to the feedback profile and providing a respective adaptive recommendation profile and adaptive consultation profile. The step of prefiltering includes the step of creating a plurality of mode-invariant concept components for each of the raw informons; and the step of filtering the raw informons includes the steps of (1) concept-based indexing of each of the mode-invariant concepts into a collection of indexed informons; and (2) creating the community profile from the collection of indexed informons.

One embodiment of the present invention provides an information filtering apparatus in a computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein. The apparatus includes an extraction means for identifying and extracting the raw informons from the data stream, each of the informons having informon content, at least one of the raw informons being of interest to a user having a user profile, the user being a member of a network community having a

community profile, at least a portion of each of the user profile and the community profile creating an adaptive collaboration profile, the extracting means being coupled to the computer network. The apparatus also includes filter means for adaptively filtering the raw informons responsive to the adaptive collaboration profile and an adaptive content profile and producing a proposed informon thereby, the informon content being filtered according to the adaptive content profile, the filter means being coupled with the extraction means. Additionally, the apparatus includes communication means for conveying the proposed informon to the user and receiving a feedback response therefrom, with the feedback response corresponding to a feedback profile, the communication means being coupled with the filter means.

Profile adaptation is accomplished by a first adaptation means for adapting at least one of the collaboration profile and the content profile responsive to the feedback profile, the first adaptation means being coupled to the filter means. The first adaptation means includes a prediction means for predicting a response of the user to a proposed informon, the prediction means receiving a plurality of temporally-spaced feedback profiles and predicting at least a portion of a future one of the adaptive collaboration profile and the adaptive content

profile in response thereto. Also included are computer storage means for storing the adaptive collaborative profile and the adaptive content profile, the storage means being coupled to the filter means.

The apparatus also includes second adaptation means for adapting at least one of the user profile responsive to at least one of the community profile and the adaptive content profile, and the community profile responsive to at least one of the user profile and the content profile, and the content profile responsive to at least one of the user profile and the community profile. It is preferred that the prediction means is a self-optimizing prediction means using a preselected learning technique, and that learning technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, a probabilistic learning technique, and a neural network learning technique.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 is an diagrammatic representation of an embodiment of an information filtering apparatus according to the present invention.

Figure 2 is an diagrammatic representation of another embodiment of an information filtering apparatus according to the present invention.

Figure 3 is a flow diagram for an embodiment of an information filtering method according to the present invention.

Figure 4 is a flow diagram for another embodiment of an information filtering method according to the present invention.

Figure 5 is a flow diagram for yet another embodiment of an information filtering method according to the present invention.

Figure 6 is an illustration of a three-component-input model and profile with associated predictors.

Figure 7 is an illustration of a mindpool hierarchy.

DETAILED DESCRIPTION OF THE EMBODIMENTS

The invention herein provides an apparatus and method for information filtering in a computer system receiving a data stream from a computer network, in which entities of information relevant to the user, or "informons," are extracted from the data stream using content-based and collaborative filtering. The invention is both interactive and distributed in structure and method. It is interactive in that communication is substantially bi-directional at

each level of the invention. It is distributed in that all or part of the information filter can include a purely hierarchical (up-and-down/parent-child) structure or method, a purely parallel (peer-to-peer) structure or method, or a combination of hierachical and parallel structures and method. The invention also provides a computer program product that implements selected embodiments of the apparatus and method.

As used herein, the term "informon" comprehends an information entity of potential or actual interest to a particular user. In general, informons can be heterogenous in nature and can be all or part of a textual, a visual, or an audio entity. Also, informons can be composed of a combination of the aforementioned entities, thereby being a multimedia entity. Furthermore, an informon can be an entity of patterned data, such as, for example, a data file containing a digital representation of signals and can be a combination of any of the previously-mentioned entities. Although some of the data in a data stream, including informons, may be included in an informon, not all data is relevant to a user, and is not within the definition of an informon. By analogy, an informon may be considered to be a "signal," and the total data stream may be considered to be "signal + noise." Therefore, an information filtering apparatus is analogous to other types of signal filters in

that it is designed to separate the "signal" from the "noise."

Also as used herein, the term "user" is an individual in communication with the network. Because an individual user can be interested in multiple categories of information, the user can be considered to be multiple clients each having a unique profile, or set of attributes. Each member client profile, then, is representative of a particular group of user preferences. Collectively, the member client profiles associated with each user is the user profile. The present invention can apply the learned knowledge of one of a user's member clients to others of the user's member clients, so that the importance of the learned knowledge, e.g., the user's preference for a particular author in one interest area as represented by the member client, can increase the importance of that particular factor, A's authorship, for others of the user's member clients. Each of the clients of one user can be associated with the individual clients of other users insofar as the profiles of the respective clients have similar attributes. A "community" is a group of clients, called member clients, that have similar member client profiles, i.e., that share a subset of attributes or interests. In general, the subset of shared attributes forms the community profile for a given

community and is representative of the community norms, or common client attributes.

The "relevance" of a particular informon broadly describes how well it satisfies the user's information need. The more relevant an informon is to a user, the higher the "signal" content. The less relevant the informon, the higher the "noise" content. Clearly, the notion of what is relevant to a particular user can vary over time and with context, and the user can find the relevance of a particular informon limited to only a few of the user's potentially vast interest areas. Because a user's interests typically change slowly, relative to the data stream, it is preferred to use adaptive procedures to track the user's current interests and follow them over time. Provision, too, is preferred to be made for sudden changes in interest, e.g., taking up antiquarian sword collecting and discontinuing stamp collecting, so that the method and apparatus track the evolution of "relevance" to a user and the communities of which the user is a member. In general, information filtering is the process of selecting the information that a users wishes to see, i.e., informons, from a large amount of data. Content-based filtering is a process of filtering by extracting features from the informon, e.g., the text of a document, to determine the informon's relevance. Collaborative filtering, on the other hand, is the process

of filtering informons, e.g., documents, by determining what informons other users with similar interests or needs found to be relevant.

The invention employs adaptive content filters and adaptive collaborative filters, which respectively include, and respond to, an adaptive content profile and an adaptive collaboration profile. The adaptive filters each are preferred to include at least a portion of a community filter for each community serviced by the apparatus, and a portion of a member client filter for each member client of the serviced communities. For this reason, the adaptive filtering is distributed in that each of the community filters perform adaptive collaborative filtering and adaptive content filtering, even if on different levels, and even if many filters exist on a given level. The integrated filtering permits an individual user to be a unique member client of multiple communities, with each community including multiple member clients sharing similar interests. The adaptive features permit the interests of member clients and entire communities to change gradually over time. Also a member client has the ability to indicate a sudden change in preference, e.g., the member client remains a collector but is no longer interested in coin collecting.

The invention also implements adaptive credibility filtering, providing member clients with a measure of

informon credibility, as judged by other member clients in the community. For example, a new member client in a first community, having no credibility, can inject an informon into the data flow, thereby providing other member clients in other communities can be provided with the proposed informon, based on the respective community profile and member client profile. If the other member clients believe the content of the informon to be credible, the adaptive credibility profile will reflect a growing credibility. Conversely, feedback profiles from informon recipients that indicate a lack of credibility cause the adaptive credibility profile, for the informon author to reflect untrustworthiness. However, the growth and declination of credibility are not "purely democratic," in the sense that one's credibility is susceptible to the bias of others' perceptions, so the growth or declination of one's credibility is generally proportional to how the credibility of the memclient is view by other member clients.

Member clients can put their respective reputations "on the line," and engage in spirited discussions which can be refereed by other interested member clients. The credibility profile further can be partitioned to permit separate credibility sub-profiles for the credibility of the content of the informon, the author, the author's community, the reviewers, and the like, and can be fed back to

discussion participants, reviewers, and observers to monitor the responses of others to the debate. The adaptive credibility profiles for those member clients with top credibility ratings in their communities may be used to establish those member clients as "experts" in their respective communities.

With this functionality, additional features can be implemented, including, for example, "instant polling" on a matter of political or consumer interest. In conjunction with both content and collaborative filtering, credibility filtering, and the resulting adaptive credibility profiles, also may be used to produce other features, such as on-line consultation and recommendation services. Although the "experts" in the communities most closely related to the topic can be afforded special status as such, member clients from other communities also can participate in the consultation or recommendation process.

In one embodiment of the consultation service, credibility filtering can be augmented to include consultation filtering. With this feature, a member client can transmit an informon to the network with a request for guidance on an issue, for example, caring for a sick tropical fish. Other member clients can respond to the requester with informons related to the topic, e.g., suggestions for water temperature and antibiotics. The

informons of the responders can include their respective credibility profiles, community membership, and professional or avocational affiliations. The requester can provide feedback to each of the responders, including a rating of the credibility of the responder on the particular topic. Additionally, the responders can accrue quality points, value tokens, or "info bucks," as apportioned by the requester, in return for useful guidance.

Similarly, one embodiment of an on-line recommendation service uses recommendation filtering and adaptive recommendation profiles to give member clients fora for obtaining recommendations on matters as diverse as local auto mechanics and world-class medieval armor refurbishers. In this embodiment, the requester can transmit the informon to the network bearing the request for recommendation. Other member clients can respond to the requester with informons having specific recommendations or dis-recommendations, advice, etc. As with the consultation service, the informons of the responders can be augmented to include their respective credibility profiles, community membership, and professional or avocational affiliations. A rating of each recommendation provided by a responder, relative to other responders' recommendations, also can be supplied. The requester can provide feedback to each of the responders, including a rating of the credibility of the

responder on the particular topic, or the quality of the recommendation. As before, the responders can accrue quality points, value tokens, or "info bucks," as apportioned by the requester, in return for the useful recommendation.

Furthermore, certain embodiments of the invention are preferred to be self-optimizing in that the some or all of the adaptive filters used in the system dynamically seek optimal values for the function intended by the filter, e.g., content analysis, collaboration, credibility, reliability, etc.

The invention herein is capable of identifying, and tracking shifts in, the preferences of individual member clients and communities, providing direct and inferential consumer preference information, whether the shifts be gradual or sudden. This consumer preference information can be used to target particular consumer preference groups, or cohorts, and provide members of the cohort with targeted informons relevant to their consumer preferences. This information also may be used to follow demographical shifts so that activities relying on accurate demographical data, such as retail marketing, can use the consumer preference information to anticipate evolving consumer needs in a timely manner.

To provide a basis for adaptation, it is preferred that each raw informon be processed into a standardized vector, which may be on the order of 20,000 to 100,000 tokens long. The learning and optimization methods that ultimately are chosen are preferred to be substantially robust to the problems which can be presented by such high-dimensional input spaces. Dimensionality reduction using methods such as the singular value decomposition (SVD), or auto-encoding neural networks attempt to reduce the size of the space while initially retaining the information contained in the original representation. However, the SVD can lose information during the transformation and may give inferior results. Two adaptation/learning methods that are presently preferred include the TF-IDF technique and the MDL technique.

TF-IDF is a weighting scheme that gives emphasis to the weighting parameters for more important terms in an informon. TF represents "term frequency," or the number of times a particular term occurs in a given informon. This is but one factor used in developing the weighting. IDF represents "inverse-document-frequency," which is a measure of how often a particular term appears across in a group of informons. Typically, common words have a low IDF, and unique terms will have a high IDF.

The TF-IDF weighting technique employs two empirical observations regarding text. First, the more times a token t appears in a document d (called the term frequency, or $tf_{t,d}$), the more likely it is that t is relevant to the topic of d. Second, the more times t occurs throughout all documents (called the document frequency or df_t), the more poorly t discriminates between documents. For a given document, these two terms can be combined into weights by multiplying the tf by the inverse of the df (i.e., idf) for each token. Often, the logarithm of tf or idf is taken in order to de-emphasize the increases in weight for larger values.

One weight used for token t in document d is:

$$w(t,d) = tf_{t,d} \log(|\ N\ | / df_t)$$

where N is the entire set of documents. The way in which TF-IDF vectors are compared also takes advantage of the domain. Because documents usually contain only a small fraction of the total vocabulary, the significance of a word appearing is much greater than of it not appearing. To emphasize the stronger information content in a word appearing, the cosine of the angle between vectors is used to measure the similarity between them. The effect of this cosine similarity metric can be better understood by the following example. Suppose two documents each contain a single word, but the words are different. The similarity of

the documents then would be zero, because the cosine of the angle between two perpendicular vectors is zero. A more unbiased learning technique that did not take advantage of this domain feature usually would group the two documents as being very similar because all but two of the elements in the lengthy vectors agreed (i.e. they were zero).

Using TF-IDF and the cosine similarity metric, there are many ways to then classify documents into categories, as recognized by a skilled artisan. For example, any of the family of nearest-neighbor techniques could be used. In the present invention, the informons in each category can be converted into TF-IDF vectors, normalized to unit length, and then averaged to get a prototype vector for the category. The advantages to taking this approach include an increased speed of computation and a more compact representation. To classify a new document, the document can be compared with each prototype vector and given a predicted rating based on the cosine similarities to each category rating. In this step, the results can be converted from a categorization procedure to a continuous value, using a linear regression.

Probabilistic techniques consider the probability that a particular term, or concept, that occurs in an informon, or that the informon satisfies the user's information need. Minimum description length, or MDL, is a probabilistic

technique that attempts to minimize the description length of an entire data set. The MDL principle can be applied to measure the overall "quality" and "cost" of a predicted data set, or model, and to optimize both quality and cost, striking a balance between the quality of the prediction and the complexity cost for achieving that quality.

The Minimum Description Length (MDL) Principle provides an information-theoretic framework for balancing the tradeoff between model complexity and training error. In the present invention's domain, this tradeoff involves how to weight each token's importance and how to decide which tokens should be left out of the model for not having enough discriminatory power. The MDL principle is based Bayes' Rule:

$$p(H|D) = \frac{p(D|H)\,p(H)}{p(D)}$$

Generally, it is desirable to find hypothesis H that maximizes $p(H|D)$, i.e. the probability of H given the observed data D. By Bayes' Rule, this is equivalent to maximizing $p(D|H)p(H)/p(D)$, because $p(D)$ is essentially independent of H, $p(D|H)p(H)$ can be maximized; or, equivalently,

$$-\log(p(D|H))-\log(p(H))$$

can be maximized from information theory principles,

$-\log_2(p(X))$ is equal to the size in bits of encoding event X in an optimal binary code. Therefore, the MDL interpretation of the above expression is that, to find the most probable hypothesis given the data, the hypothesis which minimizes the total encoding length should be found. This encoding length is equal to the number of bits required to encode the hypothesis, plus the bits required to encode the data given the hypothesis. Given a document D with token vector T_d (containing l_d non-zero unique tokens in the informon) and training data D_{train}, the most probable category c_i for d is that which minimizes the bits needed to encode T_d plus c_i:

$$\arg\max_{c_i}[p(c_i|T_d, l_d, D_{train})]$$

$$= \arg\min_{c_i}[-\log(p(T_d|c_i, l_d, D_{train}))-\log(p(c_i|l_d, D_{train}))]$$

The data independence assumption is that the probability of the data in an informon or document, given its length and category, is the product of the individual token probabilities, is

$$p(T_d|c_i, l_d, D_{train}) = \prod p(t_{i,d}|c_i, l_d, D_{train})$$

where $t_{i,d}$ is a binary value indicating whether or not the token i occurred at least once in document d.

Generally, one way to derive a probability estimate for $t_{.,d}$ while avoiding a computationally expensive optimization

step for the model parameters is to compute the following additional statistics from the training data, and use them as the parameters in the model:

$$t_i = \sum_{j \in N} t_{i,j}$$

Where t_i is the number of documents containing token i, and

$$r_{i,l}$$

Where $r_{i,l}$ is a correlation estimate [0-1] between $t_{i,d}$ and l_d.

Each statistic can be computed for each concept, and for the total across all concepts. The objective is to establish a general "background" distribution for each token, and a category-specific distribution. If the token distribution is a simple binomial, independent of document length

$$p(t_{i,d} = 0 | [c_k]) = 1 - t_i[, c_k] / |N_{[c_k]}|$$

However, if the token probability is dependent on document length, the following approximation is valid.

$$p(t_{i,d} = 0 | l_d[, c_k]) = (1 - t_i[, c_k] / \sum_{j \in N[c_k]} l_j)^{l_d}$$

The above two distributions can then be combined in a mixture model by weighting them with $t_{i,d}$ to provide:

$$p(t_{i,d} = 0 | l_d[, c_k]) = (1 - t_{i[c_k]} / N_{[c_k]})^{1 - r_{i,k}} \; X \; (1 - t_{i[c_k]} / \sum_{j \in N_{[c_k]}}^{l_j})^{l_{d x t_i}, l}$$

By hypothesizing that each token either truly has a specialized distribution for a category, or that the token is unrelated to that category and just exhibits random background fluctuations, the MDL criteria for making the decision between these hypotheses is to choose the category-specific hypothesis if the total bits saved in using this hypothesis, or total bits =

$$Total\ bits = \sum_{d \in Nc_k} -\log(p(t_{i,d}|l_d)) - [-\log(p(t_{i,d}|l_d, c_k))]$$

is greater than the complexity cost of including the extra category-specific parameters.

An additional pragmatic advantage to this probabilistic model choice is that when the logs are taken of the probabilities to get costs in bits, the probability calculation for each article's words becomes a simple, linear one that can be computed in $O(l_d)$, rather than the longer $O(|\text{dictionary}|)$. This is due to the ability to precompute the sum of the bits required to encode no words

occurring. From this sum the bits required for an actual document can quickly be computed.

One method for learning at least one of the TF-IDF and the MDL approaches can employ the following steps:

1. Divide the articles into training and unseen test sets.
2. Parse the training articles, throwing out tokens occurring less than a preselected threshold.
3. For TF-IDF, also throw out the F most frequent tokens over the entire training set.
4. Compute t_i and $r_{i,1}$ for each token.
5. For TF-IDF, compute the term weights, normalize the weight vector for each informon A, and find the average of the vectors for each rating category M.
6. For MDL, decide for each token t and category c whether to use p(t/l,c)=p(t/l), or use a community dependent model for when t occurs in c. Then pre-compute the encoding lengths for no tokens occurring for informons in each community.
7. For TF-IDF, compute the similarity of each training informon to each rating category prototype using, for example, the cosine similarity metric.
8. For MDL, compute the similarity of each training informon to each rating category by taking the inverse of the number of bits needed to encode T_d under the community's probabilistic model.

9. Using the similarity measurements computed in steps 7 or 8 on the training data, compute a linear regression from rating community similarities to continuous rating predictions.

10. Apply the model obtained in steps 7-9 similarly to test informons.

Figure 1 illustrates one embodiment of an information filtering apparatus 1 according to the invention herein. In general, a data stream is conveyed through network 3, which can be a global internetwork. A skilled artisan would recognized that apparatus 1 can be used with other types of networks, including, for example, an enterprise-wide network, or "intranet." Using network 3, User #1 (5) can communicate with other users, for example, User #2 (7) and User #3 (9), and also with distributed network resources such as resource #1 (11) and resource #2 (13).

Apparatus 1 is preferred to be part of computer system 16, although User #1 (5) is not required to be the sole user of computer system 16. In one present embodiment, it is preferred that computer system 16 having information filter apparatus 1 therein filters information for a plurality of users. One application for apparatus 1, for example, could be that user 5 and similar users may be subscribers to a commercial information filtering service, which can be provided by the owner of computer system 16.

Extraction means 17 can be coupled with, and receives data stream 15 from, network 3. Extraction means 17 can identify and extract raw informons 19 from data stream 15. Each of the raw informons 19 have an informon content. Extraction means 17 uses the adaptive content filter, and at least part of the adaptive content profile, to analyze the data stream for the presence of informons. Raw informons are those data entities whose content identifies them as being "in the ballpark," or of potential interest to a community coupled to apparatus 1. Extraction means 17 can remove duplicate informons, even if the informons arrive from different sources, so that user resources are not wasted by handling and viewing repetitive and cumulative information. Extraction means 17 also can use at least part of the community profile and the user profile for User #1 (5) to determine whether the informon content is relevant to the community of which User #1 is a part.

Filter means 21 adaptively filters raw informons 19 and produces proposed informons 23 which are conveyed to User #1 (5) by communication means 25. A proposed informon is a selected raw informon that, bases upon the respective member client and community profiles, is predicted to be of particular interest to a member client of User 5. Filter means 21 can include a plurality of community filters 27a,b and a plurality of member client filters 28a-e, each

respectively having community and member client profiles. When raw informons 19 are filtered by filter means 21, those informons that are predicted to be suitable for a particular member client of a particular community, e.g., User #1 (5), responsive to the respective community and member client profiles, are conveyed thereto. Where such is desired, filter means 21 also can include a credibility filter 35 which enables means 21 to perform credibility filtering of raw informons 19 according to a credibility profile.

It is preferred that the adaptive filtering performed within filter means 21 by the plurality of filters 27a,b, 28a-e, and 35, use an self-optimizing adaptive filtering so that each of the parameters processed by filters 27a,b, 28a-e, and 35, is driven continually to respective values corresponding to a minimal error for each individual parameter. Self-optimization encourages a dynamic, marketplace-like operation of the system, in that those entities having the most desirable value, e.g., highest credibility, lowest predicted error, etc., are favored to prevail.

Self-optimization can be effected according to respective preselected self-optimizing adaptation technique including, for example, one or more of a top-key-word-selection adaptation technique, a nearest-neighbor adaptation technique, a term-weighting adaptation technique,

a probabilistic adaptation technique, and a neural network learning technique. In one present embodiment of the invention, the term-weighting adaptation technique is preferred to be a TF-IDF technique and the probabilistic adaptation technique is preferred to be a MDL technique.

When user 5 receives proposed informon 23 from apparatus 1, user 5 is provided with multiple feedback queries along with the proposed informon. By answering, user 5 creates a feedback profile that corresponds to feedback response 29. User feedback response 29 can be active feedback, passive feedback, or a combination. Active feedback can include the user's numerical rating for an informon, hints, and indices. Hints can include like or dislike of an author, and informon source and timeliness. Indices can include credibility, agreement with conyent or author, humor, or value. Feedback response 29 provides an actual response to proposed informon 23, which is a measure of the relevance of the proposed informon to the information need of user 5. Such relevance feedback attempts to improve the performance for a particular profile by modifying the profiles, based on feedback response 29.

The predicted response anticipated by adaptive filtering means 21 can be compared to the actual feedback response 29 of user 5 by first adaptation means 30, which derives a prediction error. First adaptation means 30 also

can include prediction means 33, which collects a number of temporally-spaced feedback responses, to update the adaptive collaboration profile, the adaptive content profile, or both, with an adapted future prediction 34, in order to minimize subsequent prediction errors by the respective adaptive collaboration filter and adaptive content filter.

In one embodiment of the invention herein, it is preferred that prediction means 33 be a self-optimizing prediction means using a preselected learning technique. Such techniques can include, for example, one or more of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, and a probabilistic learning technique. First adaptation means 30 also can include a neural network therein and employ a neural network learning technique for adaptation and prediction. In one present embodiment of the invention, the term-weighting learning technique is preferred to be a TF-IDF technique and the probabilistic learning technique is preferred to be a MDL learning technique.

First adaptation means 30 further can include second adaptation means 32 for adapting at least one of the adaptive collaboration profiles, the adaptive content profiles, the community profile, and the user profile, responsive to at least one of the other profiles. In this

manner, trends attributable to individual member clients, individual users, and individual communities in one domain of system 16 can be recognized by, and influence, similar entities in other domains, contained within system 16 to the extent that the respective entities share common attributes.

Apparatus 1 also can include a computer storage means 31 for storing the profiles, including the adaptive collaborative profile and the adaptive collaboration profile. Additional trend-tracking information can be stored for later retrieval in storage means 31, or may be conveyed to network 3 for remote analysis, for example, by User #2 (7).

Figure 2 illustrates another preferred embodiment of information filtering apparatus 50, in computer system 51. Apparatus 50 can include first processor 52, second processor 53a,b, third processor 64a-d, and a fourth processor 55, to effect the desired information filtering. First processor 52 can be coupled to, and receive a data stream 56 from, network 57. First processor 52 can serve as a pre-processor by extracting raw informons 58 from data stream 56 responsive to preprocessing profile 49 and conveying informons 58 to second processor 53a,b.

Because of the inconsistencies presented by the nearly-infinite individual differences in the modes of conceptualization, expression, and vocabulary among users,

even within a community of coinciding interests, similar notions can be described with vastly different terms and connotations, greatly complicating informon characterization. Mode variations can be even greater between disparate communities, discouraging interaction and knowledge-sharing among communities. Therefore, it is particularly preferred that processor 52 create a mode-invariant representation for each raw informon, thus allowing fast, accurate informon characterization and collaborative filtering. Mode-invariant representations tend to facilitate relevant informon selection and distribution within and among communities, thereby promoting knowledge-sharing, thereby benefitting the group of interlinked communities, i.e., a society, as well.

First processor 52 also can be used to prevent duplicate informons, e.g., the same information from different sources, from further penetrating, and thus consuming the resources of, the filtering process. Other processors 53,a,b, 54a-d, also may be used to perform the duplicate information elimination function, but additionally may measure the differences between the existing informon and new informons. That difference between the content of the informon the previous time the user reviewed it and the content of the informon in its present form is the "delta" of interest. Processors 53a,b, 54a-d may eliminate the

informon from further processing, or direct the new, altered informon to the member client, in the event that nature or extent of the change exceeds a "delta" threshold. In general, from the notion of exceeding a preselected delta threshold, one may infer that the informon has changed to the extent that the change is interesting to the user. The nature of this change can be shared among all of a user's member clients. This delta threshold can be preselected by the user, or by the preselected learning technique. Such processing, or "delta learning" can be accomplished by second processor 53a,b, alone or in concert with third processor 54a-d. Indeed, third processor 54a-d can be the locus for delta learning, where processor 54a-d adapts a delta learning profile for each member client of the community, i.e. user, thus anticipating those changes in existing informons that the user may find "interesting."

Second processor 53a,b can filter raw informons 58 and extract proposed community informons 59a,b therefrom. Informons 59a,b are those predicted by processor 53a,b to be relevant to the respective community, in response to a community profile 48a,b that is unique to each of the communities. Although only two second processors 53a,b are shown in Figure 2, system 51 can be scaled to support many more processors, and communities. It is presently preferred that second processor 53a,b extract community informons

59a,b using a two-step process. Where processor 52 has generated mode-invariant concept representations of the raw informons, processor 53a,b can perform concept-based indexing, and then provide detailed community profiling of each informon.

Third processor 54a-d can receive community informons 59a,b from processor 53a,b, and extract proposed member client informons 61a-d therefrom, responsive to unique member client profiles 62a-d for respective ones of member clients 63a-d. Each user can be represented by multiple member clients in multiple communities. For example, each of users 64a,b can maintain interests in each of the communities serviced by respective second processors 53a,b, and each receive separate member client informons 61b,c and 61a,d, respectively.

Each member client 63a-d provides respective member client feedback profiles 65a-d to fourth processor 55, responsive to the proposed member client informons 61a-d. Based upon the member client feedback profiles 65a-d, processor 55 updates at least one of the preprocessing profile 49, community profiles 48a,b and member client profiles 62a-d, responsive to the member client feedback profiles 65a-d. Also, processor 55 adapts at least one of the adaptive content profile 68 and the adaptive

collaboration profile 69, responsive to profiles 49, 48a,b, and 62a-d.

Fourth processor 55 can include a plurality of adaptive filters 66a-d for each of the aforementioned profiles and computer storage therefor. It is preferred that the plurality of adaptive filters 66a-d be self-optimizing adaptive filters. Self-optimization can be effected according to a respective preselected self-optimizing adaptation technique including, for example, one or more of a top-key-word-selection adaptation technique, a nearest-neighbor adaptation technique, a term-weighting adaptation technique, and a probabilistic adaptation technique. Apparatus 50 also may include a neural network as one or more of adaptive filter 66a-d. In one present embodiment of the invention, the term-weighting adaptation technique is preferred to be a TF-IDF technique and the probabilistic adaptation technique is preferred to be a MDL technique.

An artisan would recognize that one or more of the processors 52-55 could be combined functionally so that the actual number of processors used in apparatus could be less than, or greater than, that illustrated in Figure 2. For example, in one embodiment of the present invention, first processor 52 can be in a single microcomputer workstation, with processors 53-55 being implemented in additional microcomputer systems. Suitable microcomputer systems can

include those based upon the Intel® Pentium-Pro™ microprocessor. In fact, the flexibility of design presented by the invention allows for extensive scalability of apparatus 50, in which the number of users, and the communities supported may be easily expanded by adding suitable processors. As described in the context of Figure 1, the interrelation of the several adaptive profiles and respective filters allow trends attributable to individual member clients, individual users, and individual communities in one domain of system 51 to be recognized by, and influence, similar entities in other domains, of system 51 to the extent that the respective entities in the different domains share common attributes.

The invention herein also comprehends a method 100 for information filtering in a computer system, as illustrated in Figure 3, which includes providing a dynamic informon characterization (step 105) having a plurality of profiles encoded therein, including an adaptive content profile and an adaptive collaboration profile; and adaptively filtering the raw informons (step 110) responsive to the dynamic informon characterization, thereby producing a proposed informon. The method continues by presenting the proposed informon to the user (step 115) and receiving a feedback profile from the user (step 120), responsive to the proposed informon. Also, the method includes adapting at least one

of the adaptive content profile (step 125) and the adaptive collaboration profile responsive to the feedback profile; and updating the dynamic informon characterization (step 130) responsive thereto.

The adaptive filtering (step 110) in method 100 can be distributed adaptive filtering that includes community filtering (step 135), producing a community profile for each community, and client filtering (step 140), similarly producing a member client profile for each member client of each community. It is preferred that the filtering at steps 135 and 140 be responsive to the adaptive content profile and the adaptive collaboration profile. Method 100 comprehends servicing multiple communities and multiple of users. In turn, each user may be represented by multiple member clients, with each client having a unique member client profile and being a member of a selected community. It is preferred that updating the dynamic informon characterization (step 130) further includes predicting selected subsequent member client responses (step 150).

Method 100 can also include credibility filtering (step 155) of the raw informons responsive to an adaptive credibility profile and updating the credibility profile (step 160) responsive to the feedback profile. Method 100 further can include creating a consumer profile (step 165) responsive to the feedback profile. In general, the

consumer profile is representative of predetermined consumer preference criteria relative to the communities of which the user is a member client. Furthermore, grouping selected ones (step 170) of the users into a preference cohort, responsive to the preselected consumer preference criteria, can facilitate providing a targeted informon (step 175), such as an advertisement, to the preference cohort.

Figure 4 describes yet another preferred embodiment of method 200, according to the invention herein. In general, method 200 includes partitioning (step 205) each user into multiple member clients, each having a unique member client profile with multiple client attributes and grouping member clients (step 210) to form a multiple communities with each member client in a particular community sharing selected client attributes with other member clients, thereby providing each community with a unique community profile having common client attributes.

Method 200 continues by predicting a community profile (step 215) for each community using first prediction criteria, and predicting a member client profile (step 220) for a member client in a particular community using second prediction criteria. Method 200 also includes the steps of extracting raw informons (step 225) from the data stream and selecting proposed informons (step 230) from raw informons. The proposed informons generally are correlated with one or

more of the common client attributes of a community, and of the member client attributes of the particular member client to whom the proposed informon is offered. After providing the proposed informons to the user (step 235), receiving user feedback (step 240) in response to the proposed informons permits the updating of the first and second prediction criteria (step 245) responsive to the user feedback.

Method 200 further may include prefiltering the data stream (step 250) using the predicted community profile, with the predicted community profile identifying the raw informons in the data stream.

Step 230 of selecting proposed informons can include filtering the raw informons using an adaptive content filter (step 255) responsive to the informon content; filtering the raw informons using an adaptive collaboration filter (step 260) responsive to the common client attributes for the respective community; and filtering the raw informons using an adaptive member client filter (step 265) responsive to the unique member client profile.

It is preferred that updating the first and second prediction criteria (step 245) employs a self-optimizing adaptation technique, including, for example, one or more of a top-key-word-selection adaptation technique, a nearest-neighbor adaptation technique, a term-weighting adaptation

technique, and a probabilistic adaptation technique. It is further preferred that the term-weighting adaptation technique be a TF-IDF technique and the probabilistic adaptation technique be a minimum description length technique.

In a most preferred embodiment, illustrated in Figure 5, the information filtering method according to the present invention provides rapid, efficient data reduction and routing, or filtering, to the appropriate member client. The method 300 includes parsing the data stream into tokens (step 301); creating a mode-invariant (MI) profile of the informon (step 305); selecting the most appropriate communities for each informon, based on the MI profile, using concept-based indexing (step 310); detailed analysis (step 315) of each informon with regard to its fit within each community; eliminating poor-fitting informons (step 320); detailed profiling of each informon relative to fit for each member client (step 325); eliminating poor-fitting informons (step 330); presenting the informon to the member client/user (step 335); and obtaining the member client/user response, including multiple ratings for different facets of the user's response to the informon (step 340).

In the present invention, it is preferred that coherent portions of the data stream, i.e., potential raw informons, be first parsed (step 301) into generalized words, called

tokens. Tokens include punctuation and other specialized symbols that may be part of the structure found in the article headers. For example, in addition to typical words such as "seminar" counting as tokens, the punctuation mark "$" and the symbol "Newsgroup:comp.ai" are also tokens. Using noun phrases as tokens also can be useful.

Next a vector of token counts for the document is created. This vector is the size of the total vocabulary, with zeros for tokens not occurring in the document. Using this type of vector is sometimes called the bag-of-words model. While the bag-of-words model does not capture the order of the tokens in the document, which may be needed for linguistic or syntactic analysis, that it captures most of the information needed for filtering purposes can be assumed.

Although, it is common in information retrieval systems to group the tokens together by their common linguistic roots, called stemming, as a next step it is preferred in the present invention that the tokens are left in their unstemmed form. In this form, the tokens are amenable to being classified into mode-invariant concept components.

Creating a mode-invariant profile (step 305), C, includes creating a conceptual representation for each informon, A, that is invariant with respect to the form-of-expression, e.g., vocabulary and conceptualization. Each

community can consist of a "Meta-U-Zine" collection, M, of informons. Based upon profile C, the appropriate communities, if any, for each informon in the data stream are selected by concept-based indexing (step 310) into each M. That is, for each concept C that describes A, put A into a queue Q_M, for each M which is related to C. It is preferred that there is a list of Ms that is stored for each concept and that can be easily index-searched. Each A that is determined to be a poor fit for a particular M is eliminated from further processing. Once A has been matched with a particular M, a more complex community profile P_M is developed and maintained for each M (step 315). If A has fallen into Q_M, then A is analyzed to determine whether it matches P_M strongly enough to be retained or "weeded" out (step 325) at this stage.

Each A for a particular M is sent to each user's personal agent, or member client U of M, for additional analysis based on the member client's profile (step 325). Each A that fits U's interests sufficiently is selected for U's personal informon, or "U-Zine," collection, Z. Poor-fitting informons are eliminated from placement in Z (step 330). This user-level stage of analysis and selection may be performed on a centralized server site or on the user's computer.

Next, the proposed informons are presented to user U (step 335) for review. User U reads and rates each selected A found in Z (step 340). The feedback from U can consist of a rating for how "interesting" U found A to be, as well as one or more of the following:

Opinion feedback: Did U agree, disagree, or have no opinion regarding the position of A?

Credibility Feedback: Did U find the facts, logic, sources, and quotes in A to be truthful and credible or not?

Informon Qualities: How does the user rate the informons qualities, for example, "interestingness," credibility, funniness, content value, writing quality, violence content, sexual content, profanity level, business importance, scientific merit, surprise/unexpectedness of information content, artistic quality, dramatic appeal, entertainment value, trendiness/importance to future directions, and opinion agreement.

Specific Reason Feedback: Why did the user like or dislike A?

Because of the authority?

Because of the source?

Because A is out-of-date (e.g. weather report from 3 weeks ago)?

Because the information contained in A has been seen already? (I.e., the problem of duplicate information delivery)

<u>Categorization Feedback</u>: Did U liked A? Was it placed within the correct M and Z?

Such multi-faceted feedback queries can produce rich feedback profiles from U that can be used to adapt each of the profiles used in the filtering process to some optimal operating point.

One embodiment of creating a MI profile (step 305) for each concept can include concept profiling, creation, and optimization. Broad descriptors can be used to create a substantially-invariant concept profile, ideally without the word choice used to express concept C. A concept profile can include positive concept clues (PCC) and negative concept clues (NCC). The PCC and NCC can be combined by a processor to create a measure-of-fit that can be compared to a predetermined threshold. If the combined effect of the PCC and NCC exceeds the predetermined threshold, then informon A can be assumed to be related to concept C; otherwise it is eliminated from further processing. PCC is a set of words, phrases, and other features, such as the source or the author, each with an associated weight, that tend to be in A which contains C. In contrast, NCC is a set of words, phrases, and other features, such as the source or

the author, each with an associated weight that tend to make it more unlikely that A is contained in C. For example, if the term "car" is in A, then it is likely to be about automobiles. However, if the phrase "bumper car" also is in A, then it is more likely that A related to amusement parks. Therefore, "bumper car" would fall into the profile of negative concept clues for the concept "automobile."

Typically, concept profile C can be created by one or more means. First, C can be explicitly created by user U. Second, C can be created by an electronic thesaurus or similar device that can catalog and select from a set of concepts and the words that can be associated with that concept. Third, C can be created by using co-occurrence information that can be generated by analyzing the content of an informon. This means uses the fact that related features of a concept tend to occur more often within the same document than in general. Fourth, C can be created by the analysis of collections, H, of A that have been rated by one or more U. Combinations of features that tend to occur repeatedly in H can be grouped together as PCC for the analysis of a new concept. Also, an A that one or more U have rated and determined not to be within a particular Z can be used for the extraction of NCC.

Concept profiles can be optimized or learned continually after their creation, with the objective that

nearly all As that Us have found interesting, and belonging in M, should pass the predetermined threshold of at least one C that can serve as an index into M. Another objective of concept profile management is that, for each A that does not fall into any of the one or more M that are indexed by C, the breadth of C is adjusted to preserve the first objective, insofar as possible. For example, if C's threshold is exceed for a given A, C's breadth can be narrowed by reducing PCC, increasing NCC, or both, or by increasing the threshold for C.

In the next stage of filtering, one embodiment of content-based indexing takes an A that has been processed into the set of C that describe it, and determine which M should accept the article for subsequent filtering, for example, detailed indexing of incoming A. It is preferred that a data structure including a database be used, so that the vector of Ms, that are related to any concept C, may be looked-up. Furthermore, when a Z is created by an U, the concept clues given by U to the information filter can be used to determine a set of likely concepts C that describe what U is seeking. For example, if U types in "basketball" as a likely word in the associated Z, then all concepts that have a high positive weight for the word "basketball" are associated with the new Z. If no such concepts C seem to

pre-exist, an entirely new concept C is created that is endowed with the clues U has given as the starting profile.

To augment the effectiveness of concept-based indexing, it is preferred to provide continual optimization learning. In general, when a concept C no longer uniquely triggers any documents that have been classified and liked by member clients U in a particular community M, then that M is removed from the list of M indexed into by C. Also, when there appears to be significant overlap between articles fitting concept C, and articles that have been classified by users as belonging to M, and if C does not currently index into M, then M can be added to the list of M indexed into by C. The foregoing heuristic for expanding the concepts C that are covered by M, can potentially make M too broad and, thus, accept too many articles. Therefore, it further is preferred that a reasonable but arbitrary limit is set on the conceptual size covered by M.

With regard to the detailed analysis of each informon A with respect to the community profile for each M, each A must pass through this analysis for each U subscribing to a particular M, i.e., for each member client in a particular community. After A has passed that stage, it is then filtered at a more personal, member client level for each of those users. The profile and filtering process are very similar for both the community level and the member client

level, except that at the community level, the empirical data obtained is for all U who subscribed to M, and not merely an individual U. Other information about the individual U can be used to help the filter, such as what U thinks of what a particular author writes in other Zs that the user reads, and articles that can't be used for the group-level M processing.

Figure 6 illustrates the development of a profile, and its associated predictors. Typically, regarding the structure of a profile 400, the information input into the structure can be divided into three broad categories: (1) Structured Feature Information (SFI) 405; (2) Unstructured Feature Information (UFI) 410; and (3) Collaborative Input (CI) 415. Features derived from combinations of these three types act as additional peer-level inputs for the next level of the rating prediction function, called (4) Correlated-Feature, Error-Correction Units (CFECU) 420. From inputs 405, 410, 415, 420, learning functions 425a-d can be applied to get two computed functions 426a-d, 428a-d of the inputs. These two functions are the Independent Rating Predictors (IRP) 426a-d, and the associated Uncertainty Predictors (UP) 428a-d. IRPs 426a-d can be weighted by dividing them by their respective UPs 428a-d, so that the more certain an IRP 426a-d is, the higher its weight. Each weighted IRP 429a-d is brought together with other IRPs 429a-d in a combination

function 427a-d. This combination function 427a-d can be from a simple, weighted, additive function to a far more complex neural network function. The results from this are normalized by the total uncertainty across all UPs, from Certain = zero to Uncertain = infinity, and combined using the Certainty Weighting Function (CWF) 430. Once the CWF 430 has combined the IRPs 426a-d, it is preferred that result 432 be shaped via a monotonically increasing function, to map to the range and distribution of the actual ratings. This function is called the Complete Rating Predictor (CRP) 432.

SFI 405 can include vectors of authors, sources, and other features of informon A that may be influential in determining the degree to which A falls into the categories in a given M. UFI 410 can include vectors of important words, phrases, and concepts that help to determine the degree to which A falls into a given M. Vectors can exist for different canonical parts of A. For example, individual vectors may be provided for subject/headings, content body, related information in other referenced informons, and the like. It is preferred that a positive and negative vector exists for each canonical part.

CI 415 is received from other Us who already have seen A and have rated it. The input used for CI 415 can include, for example, "interestingness," credibility, funniness,

content value, writing quality, violence content, sexual content, profanity level, business importance, scientific merit, surprise/unexpectedness of information content, artistic quality, dramatic appeal, entertainment value, trendiness/importance to future directions, and opinion agreement. Each CFECU 420 is a unit that can detect sets of specific feature combinations which are exceptions in combination. For example, author X's articles are generally disliked in the Z for woodworking, except when X writes about lathes. When an informon authored by X contains the concept of "lathes," then the appropriate CFECU 420 is triggered to signal that this is an exception, and accordingly a signal is sent to offset the general negative signal otherwise triggered because of the general dislike for X's informons in the woodworking Z.

An exemplary of the form of Structured Feature Information (SFI) 405 can include fields such as Author, Source, Information-Type, and other fields previously identified to be of particular value in the analysis. For simplicity, the exemplary SFI, below, accounts only for the Author field. For this example, assume three authors A, B, and C, have collectively submitted 10 articles that have been read, and have been rated as in TABLE 1. In the accompanying rating scheme, a rating can vary between 1 and 5, with 5 indicating a "most interesting" article. If four

new articles (11, 12, 13, 14) arrive that have not yet been rated, and, in addition to authors A, B, C, and a new author D has contributed, a simple IRP for the Author field, that just takes sums of the averages, would be as follows:

```
IRP(author) = weighted sum of
     average(ratings given the author so far)
     average(ratings given the author so far in this M)
     average(ratings given all authors so far in this M)
     average(ratings given all authors)
     average(ratings given the author so far by a particular
               user U)*
     average(ratings given the author so far in this M by a
               particular user U)*
     average(ratings given all authors so far in this M by a
               particular user U)*
     average(ratings given all authors by a particular
               user)*
```

* (if for a personal Z)

The purpose of the weighted sum is to make use of broader, more general statistics, when strong statistics for a particular user reading an informon by a particular author, within a particular Z may not yet be available. When stronger statistics are available, the broader terms can be eliminated by using smaller weights. This weighting scheme is similar to that used for creating CWFs 130, for the profiles as a whole. Some of the averages may be left out in the actual storage of the profile if, for example, an author's average rating for a particular M is not "significantly" different from the average for the author across all Ms. Here, "significance" is used is in a

statistical sense, and frameworks such as the Minimum Description Length (MDL) Principle can be used to determine when to store or use a more "local" component of the IRP. As a simple example, the following IRP employs only two of the above terms:

```
IRP(author) = weighted sum of
     average (ratings given this author so far in this M)
     average (ratings given all authors so far in this M)
```

Table 2 gives the values attained for the four new articles.

Uncertainty Predictions (UP) 428a-1 can be handled according to the underlying data distribution assumptions. It is generally important to the uncertainty prediction that it should approach zero (0) as the IRP 426a-d become an exact prediction, and should approach infinity when there is no knowledge available to determine the value of an IRP. As an example, the variance of the rating can be estimated as the UP. As recognized by a skilled artisan, combining the variances from the components of the IRP can be done using several other methods as well, depending upon the theoretical assumptions used and the computational efficiency desired. In the present example, shown in Table 3, the minimum of the variances of the components can be used. In the alternative, the UP 428a-1 can be realized by:

$$UP_{alt} = \frac{1}{\frac{1}{VAR1} + \frac{1}{VAR2}}$$

An example of Unstructured Feature Information (UFI) 410 can include entities such as text body, video/image captions, song lyrics, subject/titles, reviews/annotations, and image/audio-extracted features, and the like. Using an exemplary entity of a text body, a sample of ten (10) articles that each have some number of 4 words, or tokens, contained therewithin are listed in TABLE 4. As before, a rating can be from 1 to 5, with a rating of 5 indicating "most interesting." This vector can be any weighting scheme for tokens that allows for comparison between a group of collected documents, or informons, and a document, or informon, under question.

As previously mentioned, positive and negative vectors can provide a weighted average of the informons, according to their rating by user U. The weighting scheme can be based on empirical observations of those informons that produce minimal error through an optimization process. Continuing in the example, weighting values for the positive can be:

Rating	5	4	3	2	1
Weight	1.0	0.9	0.4	0.1	0.0

Similarly, the negative vector can use a weighting scheme in the opposite "direction":

Rating	5	4	3	2	1
Weight	0.0	0.1	0.4	0.9	1.0

Using a TF-IDF scheme, the following token vectors can be obtained:

	Token 1	Token 2	Token 3	Token 4
Positive	0.71	0.56	0.33	0.0
Negative	0.30	0.43	0.60	0.83

In the case where four new documents come in to the information filter, the documents are then compared with the profile vector.

For the purposes of the example herein, only the TF-IDF representation and the cosine similarity metric, i.e., the normalized dot product, will be used. TABLE 5 illustrates the occurrences of each exemplary token. TABLE 6 illustrates the corresponding similarity vector representations using a TF-IDF scheme. The similarity measure produces a result between 0.0-1.0 that is preferred to be remapped to an IRP. This remapping function could be as simple as a linear regression, or a one-node neural net. Here, a simple linear transformation is used, where

$$IRP(pos) = 1 + (SIM(pos)) \times 4$$

and

$$IRP(neg) = 5 - (SIM(pos)) \times 4$$

TABLE 7 illustrates both IRP(pos) and IRP(neg), along with respective positive and negative squared-error, using the 14

articles, or informons, read and rated thus far in the ongoing examples.

It is preferred that an estimate of the uncertainty resulting from a positive or negative IRP be made, and a complex neural net approach could be used. However, a simpler method, useful for this example, is simply to repeat the same process that was used for the IRP but, instead of predicting the rating, it is preferred to predict the squared-error, given the feature vector. The exact square-error values can be used as the informon weights, instead of using a rating-weight lookup table. A more optimal mapping function could also be computed, if indicated by the application.

	Token 1	Token 2	Token 3	Token 4
IRP pos. vector	16.68	8.73	12.89	11.27
IRP neg. vector	15.20	8.87	4.27	5.04

The UPs then can be computed in a manner similar to the IRP's: comparisons with the actual document vectors can be made to get a similarity measure, and then a mapping function can be used to get an UP.

Making effective use of collaborative input (CI) from other users U is a difficult problem because of the following seven issues. First, there generally is no *a priori* knowledge regarding which users already will have rated an informon A, before making a prediction for a user U, who hasn't yet read informon A. Therefore, a model for prediction must be operational no matter which subset of the

inputs happen to be available, if any, at a given time. Second, computational efficiency must be maintained in light of a potentially very large set of users and informons. Third, incremental updates of rating predictions often are desired, as more feedback is reported from users regarding an informon. Fourth, in learning good models for making rating predictions, only very sparse data typically is available for each users rating of each document. Thus, a large "missing data" problem must be dealt with effectively.

Fifth, most potential solutions to the CI problem require independence assumptions that, when grossly violated, give very poor results. As an example of an independence assumption violation, assume that ten users of a collaborative filtering system, called the "B-Team," always rate all articles exactly in the same way, for example, because they think very much alike. Further assume that user A's ratings are correlated with the B-Team at the 0.5 level, and are correlated with user C at the 0.9 level. Now, suppose user C reads an article and rates it a "5". Based on that C's rating, it is reasonable to predict that A's rating also might be a "5". Further, suppose that a member of the B-Team reads the article, and rates it a "2". Existing collaborative filtering methods are likely to predict that A's rating R_A would be:

$$R_A = (0.9 \times 5 + 0.5 \times 2)/(0.9 + 0.5) = 3.93$$

In principle, if other members of the B-Team then read and rate the article, it should not affect the prediction of A's rating, R_A, because it is known that other B-Team members always rate the article with the same value as the first member of the B-Team. However, the prediction for A by existing collaborative filtering schemes would tend to give 10 times the weight to the "2" rating, and would be:

$$R_A = (0.9 \times 5 + 10 \times 0.5 \times 2)/(0.9 + 10 \times 0.5) = 2.46$$

Existing collaborative filtering schemes do not work well in this case because B-Team's ratings are not independent, and have a correlation among one another of 1. The information filter according to the present invention can recognize and compensate for such inter-user correlation.

Sixth, information about the community of people is known, other than each user's ratings of informons. This information can include the present topics the users like, what authors the users like, etc. This information can make the system more effective when it is used for learning stronger associations between community members. For example, because Users A and B in a particular community M have never yet read and rated an informon in common, no

correlation between their likes and dislikes can be made, based on common ratings alone. However, users A and B have both read and liked several informons authored by the same author, X, although Users A and B each read a distinctly different Zs. Such information can be used to make the inference that there is a possible relationship between user A's interests and user B's interests. For the most part, existing collaborative filtering systems can not take advantage of this knowledge.

Seventh, information about the informon under consideration also is known, in addition to the ratings given it so far. For example, from knowing that informon A is about the concept of "gardening", better use can be made of which users' ratings are more relevant in the context of the information in the informon. If user B's rating agrees with user D's rating of articles when the subject is about "politics", but B's ratings agree more with user D when informon A is about "gardening", then the relationship between User B's ratings and User D's ratings are preferred to be emphasized to a greater extent than the relationship between User B and User C when making predictions about informon A.

With regard to the aforementioned fourth, sixth and seventh issues namely, making effective use of sparse, but known, information about the community and the informon, it

is possible to determine the influence of user A's rating of an informon on the predicted rating of the informon for a second user, B. For example, where user A and user B have read and rated in common a certain number of informons, the influence of user A's rating of informon D on the predicted rating of informon D for user B can be defined by a relationship that has two components. First, there can be a common "mindset," S_M, between user A and user B and informon D, that may be expressed as:

$$M_s = \text{profile(A) X profile(B) X DocumentProfile(D)}.$$

Second, a correlation may be taken between user A's past ratings and user B's past ratings with respect to informons that are similar to D. This correlation can be taken by weighting all informons E that A and B have rated in common by the similarity of E to D, S_{ED}:

$$S_{ED} = \text{Weighted\_Correlation(ratings(A),ratings(B))}$$

Each of the examples can be weighted by

$$\begin{aligned} W_{pr} &= \text{weight for rating pair (rating(A,D),rating(B,D))} \\ &= \text{DocumentProfile(E) X DocumentProfile (D)} \end{aligned}$$

Note that the "X" in the above equation may not be a mere multiplication or cross-product, but rather be a method for comparing the similarity between the profiles. Next, the similarity of the member client profiles and informon content profiles can be compared. A neural network could be used to learn how to compare profiles so that the error in predicted ratings is minimized. However, a simple cosine similarity metric, as was used earlier in the discussion of Unstructured Feature Information (UFI) can be used.

The method used is preferred to be able to include more than just the tokens, such as the author and other SFI; and, it is preferred that the three vectors for component also are able to be compared. SFIs may be handled by transforming them into an entity that can be treated in a comparable way to token frequencies that can be multiplied in the standard token frequency comparison method, which would be recognized by a skilled artisan.

Continuing in the ongoing example, the Author field may be used. Where user A and user B have rated authors K and L, the token frequency vector may appear as follows:

User	Avg. Rating Given to Author K	# in sample	Avg. Rating Given to Author L	# in sample	Avg. Rating Given to Author M	# in sample
A	3.1	21	1.2	5	N/A	0
B	4	1	1.3	7	5	2

Further, the author component of the member client profiles of user A and user B may be compared by taking a special weighted correlation of each author under comparison. In general, the weight is a function F of the sample sizes for user A's and user B's rating of the author, where F is the product of a monotonically-increasing function of the sample size for each of user A and user B. Also, a simple function G of whether the informon D is by the author or not is used. This function can be: $G = q$ if so, and $G = p<q$ if not, where p and q are optimized constraints according to the domain of the filtering system. When there has been no rating of an author by a user, then the function of the zero sample size is positive. This is because the fact that the user did not read anything by the author can signify a some indication that the author might not produce an informon which would be highly rated by the user. In this case, the exact value is an increasing function H of the total articles read by a particular user so far, because it becomes more likely that the user is intentionally avoiding reading informons by that author with each subsequent article that has been read but is not prepared by the author. In general, the exact weighting function and parameters can be empirically derived rather than theoretically derived, and so is chosen by the optimization of the overall rating prediction functions. Continuing in

the present example, a correlation can be computed with the following weights for the authors K, L and M.

Author	Weight
K	F(21,1,not author) = log(21 + 1) x log(1 + 1) x G(not author) = 0.04
L	F(5,7, author or D) = log(5+1) x log(7 + 1) x G(author) = 0.70
M	F(0.2, not author) = H(26) x log(2 + 1) x G(not author) = 0.02

It is preferred that the logarithm be used as the monotonically-increasing function and that p = 1, q = 0.1. Also used are H = log(sample_size*0.1) and an assumed rating, for those authors who are unrated by a user, to the value of "2." The correlation for the author SFI can be mapped to a non-zero range, so that it can be included in the cosine similarity metric. This mapping can be provided by a simple one-neuron neural network, or a linear function such as, (correlation + 1)$^{*}P_0$. Where the P_0 is an optimized parameter used to produce the predicted ratings with the lowest error in the given domain for filtering.

An artisan skilled in information retrieval would recognize that there are numerous methods that can be used to effect informon comparisons, particularly document comparisons. One preferred method is to use a TF-IDF weighting technique in conjunction with the cosine

similarity metric. SFI including author, can be handled by including them as another token in the vector. However, the token is preferred to be weighted by a factor that is empirically optimized rather than using a TF-IDF approach. Each component of the relationship between user A's and user B's can be combined to produce the function to predict the rating of informon D for user B. The combination function can be a simple additive function, a product function, or a complex function, including, for example, a neural network mapping function, depending upon computational efficiency constraints encountered in the application. Optimization of the combination function can be achieved by minimizing the predicted rating error as an objective.

In addition to determining the relationship between two user's ratings, a relationship that can be used and combined across a large population of users can be developed. This relationship is most susceptible to the aforementioned first, second, third, and fifth issues in the effective use of collaborative input. Specifically, the difficulty with specifying a user rating relationship across a large population of users is compounded by the lack of *a priori* knowledge regarding a large volume of dynamically changing information that may have unexpected correlation and therefore grossly violate independence assumptions.

In one embodiment of the present invention, it is preferred that users be broken into distributed groups called "mindpools." Mindpools can be purely hierarchical, purely parallel, or a combination of both. Mindpools can be similar to the aforementioned "community" or may instead be one of many subcommunities. These multiple hierarchies can be used to represent different qualities of an article. Some qualities that can be maintained in separate hierarchies include: interestingness; credibility; funniness; valuableness; writing quality; violence content; sexual content; profanity level; business importance; scientific merit; artistic quality; dramatic appeal; entertainment value; surprise or unexpectedness of information content; trendiness or importance to future directions; and opinion agreement. Each of these qualities can be optionally addressed by users with a rating feedback mechanism and, therefore, these qualities can be used drive separate mindpool hierarchies. Also, the qualities can be used in combinations, if appropriate, to develop more complex composite informon qualities, and more sublime mindpools.

Figure 7 illustrates one embodiment of a mindpool hierarchy 500. It is preferred that all users be members of the uppermost portion of the hierarchy, namely, the top mindpool 501. Mindpool 501 can be broken into sub-mindpools

502a-c, which separate users into those having at least some common interests. Furthermore, each sub-mindpool 502a-c can be respectively broken into sub-sub-mindpools 503a-b, 503c-d, 503e,f,g to which users 504a-g are respective members. as used herein, mindpool 501 is the parent node to sub-mindpools 502a-c, and sub-mindpools 502a-c are the respective parent nodes to sub-sub-mindpools 503a-g. Mindpools 502a-c are the child nodes to mindpool 501 and mindpools 503a-g are child nodes to respective mindpools 502a-3. Mindpools 503a-g can be considered to be end nodes. Users 505a,b can be members of sub-mindpool 502a, 502c, if such more closely matches their interests than would membership in a sub-sub-mindpool 503a-g. In general, the objective is to break down the entire population of users into subsets that are optimally similar. For example, the set of users who find the same articles about "gardening" by author A to be interesting but nevertheless found other articles by author A on "gardening" to be uninteresting may be joined in one subset.

A processing means or mindpool manager may be used to handle the management of each of the mindpools 501, 502a-c, and 503a-g. A mindpool manager performs the following functions: (1) receiving rating information from child-node mindpool managers and from those users coupled directly to the manager; (2) passing rating information or compiled

statistics of the rating information up to the manager's parent node, if such exists; (3) receiving estimations of the mindpool consensus on the rating for an informon from the manager's parent mindpool, if such exists; and (4) making estimations of the mindpool consensus on the rating for a specific informon for the users that come under the manager's domain; and (5) passing the estimations from function 4 down to either a child-node mindpool or, if the manager is an end node in the hierarchy, to the respective user's CWF, for producing the user's predicted rating. Function 4 also can include combining the estimations received from the manager's parent node, and Uncertainty Predictions can be estimated based on sample size, standard deviation, etc. Furthermore, as alluded to above, users can be allowed to belong to more than one mindpool if they don't fit precisely into one mindpool but have multiple views regarding the conceptual domain of the informon. Also, it is preferred that lateral communication between peer managers who have similar users beneath them to share estimation information. When a rating comes in from a user, it can be passed to the immediate manager(s) node above that user. It is preferred that the manager(s) first decide whether the rating will effect its current estimation or whether the statistics should be passed upward to a parent-node. If the manager estimation would change by an amount

above an empirically-derived minimum threshold, then the manager should pass that estimation down to all of its child-nodes. In the event that the compiled statistics are changed by more than another minimum threshold amount, then the compiled statistics should be passed to the manager's parent-node, if any ,and the process recurses upward and downward in the hierarchy.

Because no mindpool manager is required to have accurate information, but just an estimation of the rating and an uncertainty level, any manager may respond with a simple average of all previous documents, and with a higher degree of uncertainty, if none of its child-nodes has any rating information yet. The preferred distributed strategy tends to reduce the communication needed between processors, and the computation tends to be pooled, thereby eliminating a substantial degree of redundancy. Using this distributed strategy, the estimations tend to settle to the extent that the updating of other nodes, and the other users predictions are minimized. Therefore, as the number of informons and users becomes large, the computation and prediction updates grow as the *sum* of the number of informons and the number of users, rather than the *product* of the number of informons and the number of users. In addition, incremental updates can be accomplished by the passing of estimations up and down hierarchy. Incremental updates of rating predictions

continue to move until the prediction becomes stable due to the large sample size. The distributed division of users can reduce the effects of independent assumption violations. In the previous example with the B-Team of ten users, the B-Team can be organized as a particular mindpool. With the additional ratings from each of the B-Team members, the estimation from the B-Team mindpool typically does not change significantly because of the exact correlation between the members of that mindpool. This single estimation then can be combined with other estimations to achieve the desired result, regardless of how many B-Team members have read the article at any given time.

The mindpool hierarchies can be created by either computer- or human-guided methods. If the hierarchy creation is human-guided, there often is a natural breakdown of people based on information such as job position, common interests, or any other information that is known about them. Where the mindpool hierarchy is created automatically, because the previously described measure of the collaborative input relationship between users can be employed in a standard hierarchical clustering algorithm to produce each group of users or nodes in the mindpool hierarchy. Such standard hierarchical clustering algorithms can include, for example, the agglomerative method, or the divide-and-conquer method. A skilled artisan would

recognize that many other techniques also are available for incrementally-adjusting the clusters as new information is collected. Typically, clustering is intended to (1) bring together users whose rating information is clearly not independent; and (2) produce mindpool estimations that are substantially independent among one another.

Estimations are made in a manner similar to other estimations described herein. For example, for each user or sub-mindpool (sub-informant), a similarity between the sub-informant and the centroid of the mindpool can be computed in order to determine how relevant the sub-informant is in computing the estimation. Uncertainty estimators also are associated with these sub-informants, so that they can be weighted with respect to their reliability in providing the most accurate estimation. Optionally, the informon under evaluation can be used to modulate the relevancy of a sub-informant. This type of evaluation also can take advantage of the two previously-determined collaborative information relationship components, thereby tending to magnify relationships that are stronger for particular types of informons than for others. Once a suitable set of weights are established for each user within a mindpool for a particular informon, a simple weighted-average can be used to make the estimation. It is preferred that the "simple" weighted average used is more conservative regarding input

information that a simple independent linear regression. Also, the overall Uncertainty can be derived from the Uncertainty Predictions of the sub-informants, in a manner similar to the production of other uncertainty combination methods described above. Approximations can be made by pre-computing all terms that do not change significantly, based on the particular informon, or the subset of actual ratings given so far to the mindpool manager.

As stated previously, the correlated-feature error-correction units (CFECUs) are intended to detect irregularities or statistical exceptions. Indeed, two objectives of the CFECU units are to (1) find non-linear exceptions to the general structure of the three aforementioned types of inputs (SFI, UFI, and CI); and (2) find particular combinations of informon sub-features that statistically stand out as having special structure which is not captured by the rest of the general model; and (3) trigger an additional signal to the CFECU's conditions are met, in order to reduce prediction error. An example of the CFECU operation is given presently.

	User B's Avg. Rating of of Informons About	
	Gardening	Politics
Author A's Articles	4.5	1.2
Other Authors	1.4	2

Weighted by Topic	1.68	1.87

	User B's number of Informons Read About		
	Gardening	Politics	Average over Topics
Author A's Articles	7	40	1.69
Other Authors	70	200	1.84

In this example, it is desired that author A's informon D about gardening have a high predicted rating for user B. However, because the average rating for author A by user B is only 1.69, and the average rating for the gardening concept is only 1.68, a three-part model (SFI-UFI-CI) that does not evaluate the informon features in combination would tend to not rank informon D very highly. In this case, the first CFECU would first find sources of error in past examples. This could include using the three-part model against the known examples that user B has rated so far. In this example, seven articles that user B has rated, have an average rating of 4.5, though even the three-part model only predicts a rating of about 1.68. When such a large error appears, and has statistical strength due to the number of examples with the common characteristics of, for example, the same author and topic, a CFECU is created to identify that this exception to the three-part model has been triggered and that a correction signal is needed. Second, it is preferred to index the new CFECU into a database so that, when triggering features appear in an informon, for

example, author and topic, the correction signal is sent into the appropriate CWF. One method which can be used to effect the first step is a cascade correlation neural network, in which the neural net finds new connection neural net units to progressively reduce the prediction error. Another method is to search through each informon that has been rated but whose predicted rating has a high error, and storing the informons profile.

When "enough" informons have been found with high error and common characteristics, the common characteristics can be joined together as a candidate for a new CFECU. Next, the candidate can be tested on all the samples, whether they have a high prediction or a low prediction error associated with them. Then, the overall error change (reduction or increase) for all of the examples can be computed to determine if the CFECU should be added to the informon profile. If the estimated error reduction is greater than a minimum threshold level, the CFECU can be added to the profile. As successful CFECU are discovered for users' profiles, they also can be added to a database of CFECU's that may be useful for analyzing other profiles. If a particular CFECU has a sufficiently broad application, it can be moved up in the filtering process, so that it is computed for every entity once. Also, the particular CFECU can be included in the representation that is computed in

the pre-processing stage as a new feature. In general, the estimation of the predicted rating from a particular CFECU can be made by taking the average of those informons for which the CFECU responds. Also, the Uncertainty can be chosen such that the CFECU signal optimally outweighs the other signals being sent to the CWF. One method of self-optimization that can be employed is, for example, the gradient descent method, although a skilled artisan would recognize that other appropriate optimization methods may be used.

All publications mentioned in this specification are indicative of the level of skill in the art to which this invention pertains. All publications are herein incorporated by reference to the same extent as if each individual publication was specifically but individually indicated to be incorporated by reference.

Furthermore, many alterations and modifications may be made by those having ordinary skill in the art without departing from the spirit and scope of the invention. Therefore, it must be understood that the illustrated embodiments have been set forth only for the purposes of example, and that it should not be taken as limiting the invention as defined by the following claims. The following claims are, therefore, to be read to include not only the combination of elements which are literally set forth but

all equivalent elements for performing substantially the same function in substantially the same way to obtain substantially the same result. The claims are thus to be understood to include what is specifically illustrated and described above, what is conceptually equivalent, and also what incorporates the essential idea of the invention.

TABLE 1

Article	Author	Rating given
1	A	5
2	B	1
3	B	2
4	B	5
5	C	2
6	C	2
7	C	1
8	C	2
9	C	2
10	C	2

TABLE 2

Article	Author	avg(author)	IRP(author)	normalized weight	weight	avg(all auth)	normalized weight	weight
11	A	5.00	3.12	0.86	2.40	0.49	0.14	4.65
12	B	2.67	0.23	0.32	2.40	0.49	0.66	2.49
13	C	1.83	6.00	0.92	2.40	0.49	0.06	1.86
14	D	N/A	0.00	0.00	2.40	0.49	1.00	2.40

TABLE 3

Article [alt.]	Author	var(author)	var(all auth.)	UP(author)	UP(author)
11	A	2.25	2.04	2.04	1.07
12	B	4.33	2.04	2.04	1.39
13	C	0.17	2.04	0.17	0.15
14	D	N/A	2.04	2.04	2.04

TABLE 4

Article	Token 1	Token 2	Token 3	Token 4	Rating
1	2	-	-	-	5
2	1	2	-	-	5
3	2	2	1	-	4
4	2	-	1	-	4
5	1	-	-	1	1
6	3	1	3	1	3
7	-	1	3	1	2
8	-	-	3	2	2
9	-	2	-	2	2
10	-	-	-	2	1
Frequency	11	8	11	9	

TABLE 5

Article	Token 1	Token 2	Token 3	Token 4
11	3	-	-	-
12	1	-	1	4
13	-	5	5	-
14	-	-	-	-

TABLE 6

Article	Token 1	Token 2	Token 3	Token 4	Positive Similarity	Negative Similarity
1	0.18	0.00	0.00	0.00	0.73	0.26
2	0.09	0.25	0.00	0.00	0.80	0.44
3	0.18	0.25	0.09	0.00	0.96	0.60
4	0.18	0.00	0.09	0.00	0.81	0.49
5	0.09	0.00	0.00	0.11	0.54	0.73
6	0.27	0.13	0.27	0.11	0.89	0.85
7	0.00	0.13	0.27	0.11	0.55	0.89
8	0.00	0.00	0.27	0.22	0.33	0.91
9	0.00	0.25	0.00	0.22	0.50	0.76
10	0 00	0.00	0.00	0.22	0.10	0.73
11	0.27	0.00	0.00	0.00	0.73	0 26
12	0.09	0.00	0.09	0.44	0.31	0.86
13	0.00	0.63	0.45	0.00	0.67	0.64
14	0.00	0.00	0.00	0.00	0.50	0.50

TABLE 7

Article	IRP(pos)	IRP(neg)	Act. Rat.	sq. err.(pos)	sq. err.(neg)
1	3.93	3.95	5	1.14	1.09
2	4.19	3.25	5	0.66	3 06
3	4 84	2.61	4	0.71	1.94
4	4.23	3.03	4	0.05	0.94
5	3.18	2.09	1	4.74	1.18
6	4.58	1.61	3	2.50	1.93
7	3.21	1.44	2	1.45	0.32
8	2.31	1.37	2	0.10	0.40
9	3.01	1.96	2	1.03	0.00
10	1.41	2.09	1	0.17	1.20
11	3.93	3.95			
12	2.24	1.55			
13	3.68	2 44			
14	3.00	3.00			

WHAT IS CLAIMED IS:

1. A method for information filtering in a computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein, at least one of the raw informons being of interest to a user, the user being a member client of a community, the method comprising the steps of:

a. providing a dynamic informon characterization having a plurality of profiles encoded therein, the plurality of profiles including an adaptive content profile and an adaptive collaboration profile;

b. adaptively filtering the raw informons responsive to the dynamic informon characterization, producing a proposed informon thereby;

c. presenting the proposed informon to the user;

d. receiving a feedback profile from the user, responsive to the proposed informon;

e. adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the feedback profile; and

f. updating the dynamic informon characterization responsive to the adapting of step (e).

2. The method of Claim 1 wherein the step of adaptively filtering is distributed.

3. The method of Claim 2 wherein the step of distributed adaptively filtering includes community filtering and client filtering, thereby respectively producing a community profile and a member client profile, each of the community filtering and client filtering being responsive to the adaptive content profile and the adaptive collaboration profile, the dynamic informon characterization being adapted responsive to at least one of the community profile and the member client profile.

4. The method of Claim 3 wherein the user profile includes at least one member client profile.

5. The method of Claim 1 having a plurality of communities and a plurality of users, a plurality of clients being representative of each user, each client being a member client of a selected one of the plurality of communities and having a member client profile.

6. The method of Claim 5 wherein the step of adaptively filtering is distributed and includes the steps of:

a. community filtering the informons responsive to the adaptive content profile and the adaptive collaboration profile;

b. producing a community profile for at least one of the communities, the community profile being representative of the respective community norms;

c. client filtering the informons responsive to the adaptive content profile and the adaptive collaboration profile; and

d. producing member client profiles for selected member clients in respective communities, the member client profiles being representative of respective member client preferences; and

e. adapting the dynamic informon characterization responsive to a selected community profiles and the member client profile.

7. The method of Claim 1 wherein:

a. the feedback profile includes a plurality of user responses to the proposed informon; and

b. the step of updating the dynamic informon characterization further includes the step of predicting selected subsequent ones of the plurality of user responses.

8. The method of claim 6 wherein:

a. the feedback profile includes a plurality of member client responses to the proposed informon; and

b. the step of updating the dynamic informon characterization further includes the step of predicting selected subsequent ones of the plurality of member client responses.

9. The method of Claim 1 further comprising the steps of:

a. credibility filtering the informons responsive to an adaptive credibility profile; and

b. updating the credibility profile responsive to the feedback profile.

10. The method of Claim 8 further comprising the steps of:

a. credibility filtering informons responsive to an adaptive credibility profile; and

b. updating the credibility profile responsive to selected member client responses.

11. The method of Claim 10 wherein the step of updating the credibility profile further includes the step

of predicting selected subsequent ones of the plurality of user responses.

12. The method of Claim 1 wherein the step of adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the feedback profile further includes the step of optimally adapting the adaptive content profile and the adaptive collaboration profiles.

13. The method of Claim 12 wherein the step of optimally adapting further includes the step of self-optimizing the adaptive content profile and the collaboration profile using a selected self-optimizing technique.

14. The method of Claim 6 wherein the step of adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the feedback profile further includes the step of optimally adapting the adaptive content profile and the adaptive collaboration profile.

15. The method of Claim 14 wherein the step of optimally adapting further includes the step of self-

optimizing the adaptive content profile and the adaptive collaboration profile using a selected self-optimizing technique.

16. The method of Claim 1 wherein each of the informons includes at least one of a textual, a visual, an audio, a patterned data, and a multimedia entity.

17. The method of Claim 6 wherein each of the informons includes at least one of a textual, a visual, an audio, a patterned data, and a multimedia entity.

18. The method of Claim 3 further comprising the steps of:

a. credibility filtering the informons responsive to an adaptive credibility profile, the credibility filtering being distributed; and

b. updating the dynamic informon characterization responsive to at least one of the adaptive content profile, the adaptive collaboration profile, and the adaptive credibility profile.

19. The method of Claim 1 further comprising the step of creating a consumer profile responsive to the feedback profile, the consumer profile being representative of

predetermined consumer preference criteria relative to communities of which the user is a member client.

20. The method of Claim 1 wherein the user is one of a plurality of users, each user being a plurality of member clients, each member client being a member of a selected community and having a unique member client profile relative to the selected community, selected member clients of each of the plurality of users being grouped into preselected interest groups, responsive to the respective feedback profiles, and the adaptive collaborative profile being updated responsive to the respective feedback profiles of selected users.

21. The method of Claim 20 wherein the interest groups are representative of user interests and community norms.

22. The method of Claim 1 wherein the user provides a temporally-spaced plurality of feedback responses and the adaptive content profile is adapted therewith according to a preselected adaptation technique.

23. The method of Claim 9 wherein the user is one of a plurality of users, each user being a plurality of member clients, each member client uniquely corresponding with one

of a plurality of communities and providing a respective feedback profile, selected ones of the plurality of client members being grouped into preselected interest groups responsive to the respective feedback profiles, and the adaptive credibility profile being updated responsive to the respective feedback profiles of the selected ones.

24. The method of Claim 19 wherein the user is one of a plurality of users and the consumer profile is one of a plurality of consumer profiles, and further comprising the step of grouping selected ones of the plurality of users into a preference cohort responsive to the preselected consumer preference criteria.

25. The method of Claim 24 further comprising the step of providing a targeted informon to the preference cohort, the targeted informon corresponding to the predetermined consumer preference criteria relative to the preference cohort.

26. The method of Claim 3 wherein the dynamic informon characterization includes a prefiltering profile, an adaptive broker filtering profile, and a member client profile, and wherein the step of adaptively filtering includes the steps of:

a. prefiltering the data stream according to the prefiltering profile, thereby extracting a plurality of raw informons from the data stream, the prefiltering profile being responsive to the adaptive content profile;

b. filtering the raw informons according to the adaptive broker profile, the adaptive broker profile including the adaptive collaborative profile and the adaptive content profile; and

c. client user filtering the raw informons according to an adaptive member client profile, thereby extracting the proposed informon.

27. The method of Claim 1 wherein the dynamic informon characterization includes prediction rules and category rules, the prediction rules and the category rules being responsive to the feedback profile.

28. The method of Claim 27 further comprising the step of learning the category rules using a preselected category rule learning technique.

29. The method of Claim 27 further comprising the step of learning the prediction rule using a preselected prediction rule learning technique.

30. The method of Claim 1 wherein the step of providing the dynamic informon characterization includes generating the characterization using a preselected learning technique.

31. The method of Claim 30 wherein the preselected learning technique includes at least one of a top-keyword-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, a neural net learning technique, and a probabilistic learning technique.

32. The method of Claim 31 wherein the term-weighting learning technique is a TF-IDF technique and the probabilistic learning technique is a minimum description length technique.

33. The method of Claim 28 wherein the category rules include a plurality of category profile attributes, and each informon has a plurality of informon category attributes corresponding to respective ones of the plurality of category profile attributes, the category profile attributes being responsive to the user feedback profile, the method further comprising the steps of:

a. deriving a figure-of-merit for each of the informon category attributes relative to the category profile attributes;

b. combining the figures-of-merit using a predetermined adaptive function, thereby producing a category fitness figure-of-merit; and

c. incorporating the category fitness figure-of-merit into the dynamic informon characterization.

34. The method of Claim 33 wherein:

a. the plurality of informon attributes each include at least one of an informon keyword, a fixed informon representation, informon author, actual and predicted informon destinations, and informon feature values; and

b. the plurality of category profile attributes each include at least one of category keyword, category fixed representation, ranked category authors, category destination, recent relevant subjects, and category feature values.

35. A method for information filtering in a computer system receiving a data stream from a computer network having a plurality of users, the data stream having raw

informons embedded therein, the method comprising the steps of:

a. partitioning each user into a plurality of member clients, each member client having a unique member client profile, each profile having a plurality of client attributes;

b. grouping member clients to form a plurality of communities, each community including selected clients of the plurality of member clients, selected client attributes of ones of the selected clients being comparable to others of the selected clients thereby providing each community with a community profile having common client attributes;

c. predicting at least one community profile for each community using first prediction criteria;

d. predicting at least one member client profile for the client in a community using second prediction criteria;

e. extracting the raw informons from the data stream, each of the raw informons having an informon content;

f. selecting proposed informons from the raw informons, the proposed informons being correlated with at least one of the common client attributes and the member client attributes;

g. providing the proposed informons to the user;

h. receiving user feedback in response to the proposed informons; and

i. updating at least one of the first and second prediction criteria responsive to the user feedback.

36. The method of Claim 35 wherein the step of extracting the raw informons further comprises prefiltering the data stream using the predicted community profile, the predicted community profile identifying the raw informons in the data stream.

37. The method of Claim 35 wherein the step of selecting includes the steps of:

a. filtering the raw informons using an adaptive content filter responsive to the informon content;

b. filtering the raw informons using an adaptive collaboration filter responsive to the common client attributes for the respective community; and

c. filtering the raw informons using an adaptive member client filter responsive to the unique member client profile,

wherein the proposed informons are selected from the raw informons thereby.

38. The method of Claim 35 wherein the step of updating at least one of the first and second prediction criteria further includes updating using an optimizing adaptation technique.

39. The method of Claim 38 wherein the optimizing adaptation technique is a self-optimizing adaptation technique.

40. An information filtering apparatus in a computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein, the apparatus comprising:

a. extraction means for identifying and extracting the raw informons from the data stream, each of the informons having informon content, at least one of the raw informons being of interest to a user having a user profile, the user being a member of a network community having a community profile, at least a portion of each of the user profile and the community profile creating an

adaptive collaboration profile, the extracting means being coupled to the computer network;

b. filter means for adaptively filtering the raw informons responsive to the adaptive collaboration profile and an adaptive content profile and producing a proposed informon thereby, the informon content being filtered according to the adaptive content profile, the filter means being coupled with the extraction means;

c. communication means for conveying the proposed informon to the user and receiving a feedback response therefrom, the feedback response corresponding to a feedback profile, the communication means being coupled with the filter means;

d. first adaptation means for adapting at least one of the collaboration profile and the content profile responsive to the feedback profile, the first adaptation means being coupled to the filter means; and

e. computer storage means for storing the adaptive collaborative profile and the adaptive content profile, the storage means being coupled to the filter means.

41. The apparatus of Claim 40 wherein the first adaptation means further comprises second adaptation means for adapting at least one of the user profile responsive to at least one of the community profile and the adaptive content profile, and the community profile responsive to at least one of the user profile and the content profile, and the content profile responsive to at least one of the user profile and the community profile.

42. The apparatus of Claim 40 wherein the first adaptation means includes a prediction means for predicting a response of the user to a proposed informon, the prediction means receiving a plurality of temporally-spaced feedback profiles and predicting at least a portion of a future one of the adaptive collaboration profile and the adaptive content profile in response thereto.

43. The apparatus of Claim 42 wherein the prediction means is a self-optimizing prediction means using a preselected learning technique.

44. The apparatus of Claim 43 wherein the learning technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a

term-weighting learning technique, and a probabilistic learning technique.

45. The apparatus of Claim 43 further comprising a neural network and the preselected learning technique is a preselected neural network learning technique.

46. The apparatus of Claim 44 further comprising a neural network and the preselected learning technique also includes a preselected neural network learning technique.

47. The apparatus of Claim 40 wherein the filter means further filters the raw informon according to a credibility profile, the credibility profile being responsive to at least one of the adaptive collaboration profile and the adaptive content profile.

48. The apparatus of claim 40 wherein the computer network includes a plurality of network communities coupled with the extraction means, each network community having a plurality of users, each user corresponding to a plurality of member clients, and wherein apparatus further includes:

a. computer storage for the adaptive collaboration profile and the adaptive content profile for each of the plurality of network communities;

b. computer storage for the community profile for each of the plurality of communities and the member client profile for each of the plurality of member clients, each member client being coupled to a respective community; and

c. a plurality of adaptive filters in the filter means for each of the adaptive collaboration and adaptive content and community and member client profiles, each of the adaptive filters being responsive to a respective one of the profiles.

49. The apparatus of Claim 48 wherein selected ones of the plurality of adaptive filters are self-optimizing adaptive filters.

50. The apparatus of Claim 49 wherein each of the self-optimizing adaptive filters use a respective preselected adaptation technique.

51. The apparatus of Claim 50 wherein the respective preselected adaptation technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, and a probabilistic learning technique.

52. The apparatus of Claim 50 further comprising a neural network and the respective preselected adaptation technique is a preselected neural network learning technique.

53. The apparatus of Claim 51 further comprising a neural network and the respective preselected adaptation technique including a preselected neural network learning technique.

54. The apparatus of Claim 48 wherein the filter means further includes an adaptive credibility filter for filtering the raw informon according to a credibility profile, the credibility profile being responsive to at least one of the adaptive collaboration profile and the adaptive content profile, and the apparatus further includes computer storage for the credibility profile.

55. An information filtering apparatus in a computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein, the apparatus comprising:

a. a first processor coupled to the computer network and receiving the data stream therefrom, the first

processor extracting raw informons from the data stream, responsive to a preprocessing profile;

b. a second processor coupled to the first processor and receiving the raw informons therefrom, the second processor extracting proposed community informons from the raw informons, responsive to an a community profile;

c. a third processor coupled to the second processor and receiving the proposed community informons therefrom, the third processor extracting proposed member client informons from the proposed community informons, responsive to a member client profile;

d. a fourth processor coupled to the first, the second, and the third processor, the fourth processor

  (1) being in communication with the member client,

  (2) receiving a member client feedback profile responsive to the proposed member client informon,

  (3) adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the member client feedback profile, and

(4) updating at least one of the preprocessing profile, the community profile, and the member client profile responsive to the responsive to the adapting of the adaptive content profile and the adaptive collaboration profile.

56. The apparatus of Claim 55, further comprising:

a. computer storage for the adaptive collaboration profile and the adaptive content profile for each of a plurality of communities;

b. computer storage for the community profile for each of the plurality of communities and the member client profile for each of the plurality of member clients, each member client being coupled to a respective community; and

c. a plurality of adaptive filters in the filter means for each of the adaptive collaboration and adaptive content and community and member client profiles, each of the adaptive filters being responsive to a respective one of the profiles.

57. The apparatus of Claim 56 wherein the fourth processor further includes an adaptive credibility filter for filtering the raw informon according to an adaptive credibility profile, and wherein the step of updating includes updating the adaptive credibility profile responsive to at least one of the adaptive collaboration profile and the adaptive content profile, and the apparatus further includes computer storage for the credibility profile.

58. The apparatus of Claim 57 wherein selected ones of the plurality of adaptive filters are self-optimizing adaptive filters using a respective preselected adaptation technique.

59. The apparatus of Claim 58 wherein the respective preselected adaptation technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, and a probabilistic learning technique.

60. The apparatus of Claim 58 further comprising a neural network and the respective preselected adaptation technique is a preselected neural network learning technique.

61. The apparatus of Claim 59 further comprising a neural network and the respective preselected adaptation technique including a preselected neural network learning technique.

62. A computer program product having a computer-readable medium having computer program logic recorded thereon for information filtering in the computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein, the raw informons having informon content, the user having a user profile and being a member of a community having a community profile, the computer program product comprising:

a. means for providing a dynamic informon characterization having a plurality of profiles encoded therein, the plurality of profiles including an adaptive content profile and an adaptive collaboration profile, the adaptive content profile being responsive to the informon content, the adaptive collaboration profile being correlated with the user profile and the community profile;

b. means for adaptively filtering the raw informons responsive to the dynamic informon

characterization, producing a proposed informon thereby;

c. means presenting the proposed informon to the user;

d. means for receiving a feedback profile from the user, responsive to the proposed informon;

e. means for adapting at least one of the adaptive content profile and the adaptive collaboration profile responsive to the feedback profile; and

f. means for updating the dynamic informon characterization responsive thereto.

63. The computer program product of Claim 62 wherein the means for adaptively filtering is distributed and includes means for community filtering and means for client filtering, each of the means for community filtering and client filtering being responsive to the adaptive content profile and the adaptive collaboration profile, thereby respectively producing a community profile and a client profile, the dynamic informon characterization being adapted responsive to at least one of the community profile and the member client profile, the community profile being at least partially correlated with the member client profile.

64. The computer program product of Claim 63 further comprising means for communicating with a plurality of users and a plurality of communities, each community having a respective community profile, each user being represented by a plurality of clients, each client being a member client of a selected one of the plurality of communities and having a member client profile.

65. The computer program product of Claim 64 wherein the feedback profile includes a plurality of member client responses to the proposed informon; and further comprising means for updating the dynamic informon characterization further includes means for predicting selected subsequent ones of the plurality of member client responses.

66. The computer program product of Claim 62, further comprising:

a. means for credibility filtering the informons responsive to an adaptive credibility profile, the credibility filtering being distributed; and
b. means for updating the dynamic informon characterization responsive to at least one of the adaptive content profile, the adaptive collaboration profile, and the credibility profile.

67. The computer program product of Claim 62 wherein the means for adapting further includes means for self-optimizing the adaptive content profile and the adaptive collaboration profile using a selected self-optimizing technique, and the selected self-optimizing technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a term-weighting learning technique, a neural network technique, and a probabilistic learning technique.

68. The computer program product of Claim 62 wherein each of the informons includes at least one of a textual, a visual, an audio, a patterned data, and a multimedia entity.

69. The computer program product of Claim 62, further comprising:

a. means for creating a consumer profile responsive to the feedback profile, the consumer profile being representative of predetermined consumer preference criteria relative to the communities of which the user is a member, wherein the user is one of a plurality of users and the consumer profile is one of a plurality of consumer profiles;

b. means for grouping selected ones of the plurality of users into a preference cohort responsive to the predetermined consumer preference criteria; and

c. means for providing a targeted informon to the preference cohort, the targeted informon corresponding to the predetermined consumer preference criteria relative to the preference cohort.

70. A computer program product having a computer-readable medium having computer program logic recorded thereon for information filtering in a computer system receiving a data stream from a computer network having a plurality of users, the data stream having raw informons embedded therein, the computer program product comprising:

a. means for partitioning each user into a plurality of member clients, each member client having a unique member client profile, each profile having a plurality of client attributes;

b. means for grouping member clients to form a plurality of communities, each community including selected clients of the plurality of member clients, selected client attributes of ones of the selected clients being comparable to others of the

selected clients thereby providing each community with a community profile having common client attributes;

c. means for predicting a community profile for each community using first prediction criteria;

d. means for predicting a member client profile for each member client in a community using second prediction criteria;

e. means for extracting the raw informons from the data stream, each of the raw informons having an informon content;

f. means for selecting proposed informons from the raw informons, the proposed informons being correlated with at least one of the common client attributes and the member client attributes;

g. means for providing the proposed informons to the user;

h. means for receiving user feedback in response to the proposed informons; and

i. means for updating at least one of the first and second prediction criteria responsive to the user feedback.

71. A computer program product having a computer-readable medium having computer program logic recorded

thereon for information filtering in a computer system receiving a data stream from a computer network having a plurality of users, the data stream having raw informons embedded therein, the computer program product comprising:

a. extraction means for identifying and extracting the raw informons from the data stream, each of the informons having informon content, at least one of the raw informons being of interest to a user having a user profile, the user being a member of a network community having a community profile, at least a portion of each of the user profile and the community profile creating an adaptive collaboration profile, the extracting means being coupled to the computer network;

b. filter means for adaptively filtering the raw informons responsive to the adaptive collaboration profile and an adaptive content profile and producing a proposed informon thereby, the informon content being filtered according to the adaptive content profile, the filter means being coupled with the extraction means;

c. communication means for conveying the proposed informon to the user and receiving a feedback response therefrom, the feedback response corresponding to a feedback profile, the

communication means being coupled with the filter means;

d. first adaptation means for adapting at least one of the collaboration profile and the content profile responsive to the feedback profile, the first adaptation means being coupled to the filter means; and

e. means for storing the adaptive collaborative profile and the adaptive content profile, the means for storing being coupled to the filter means.

72. The computer program product of Claim 71 wherein the first adaptation means further comprises second adaptation means for adapting at least one of the user profile responsive to at least one of the community profile and the adaptive content profile, and the community profile responsive to at least one of the user profile and the content profile, and the content profile responsive to at least one of the user profile and the community profile.

73. The apparatus of Claim 71 wherein the first adaptation means includes a prediction means for predicting a response of the user to a proposed informon, the prediction means receiving a plurality of temporally-spaced

feedback profiles and predicting at least a portion of a future one of the adaptive collaboration profile and the adaptive content profile in response thereto.

74. The computer program product of Claim 73 wherein the prediction means is a self-optimizing prediction means using a preselected learning technique therefor.

75. The computer program product of Claim 74 wherein the preselected learning technique includes at least one of a top-key-word-selection learning technique, a nearest-neighbor learning technique, a neural network technique, a term-weighting learning technique, and a probabilistic learning technique.

76. The computer program product of Claim 75 wherein the filter means further comprises means for filtering the raw informon according to an adaptive credibility profile, the adaptive credibility profile being responsive to at least one of the adaptive collaboration profile and the adaptive content profile.

77. The method of claim 9 further comprising at least one of the step of recommendation filtering and the step of consultation filtering the raw informon responsive to the

feedback profile and providing a respective adaptive recommendation profile and adaptive consultation profile.

78. The method of claim 11 further comprising at least one of the step of recommendation filtering and the step of consultation filtering the raw informon responsive to the feedback profile and providing a respective adaptive recommendation profile and adaptive consultation profile.

79. The method of claim 18 further comprising at least one of the step of recommendation filtering and the step of consultation filtering the raw informon responsive to the feedback profile and providing a respective adaptive recommendation profile and adaptive consultation profile.

80. The method of claim 26 wherein:

a. the step of prefiltering includes the step of creating a plurality of mode-invariant concept components for each of the raw informons; and

b. the step of filtering the raw informons includes the steps of:

   (1) concept-based indexing of each of the mode-invariant concepts into a collection of indexed informons; and

(2) creating the community profile from the collection of indexed informons.

81. The method of claim 35 further comprising at least one of the step of recommendation filtering and the step of consultation filtering the raw informon responsive to the feedback profile and providing a respective adaptive recommendation profile and adaptive consultation profile.

82. The apparatus of claim 54 wherein the filter means further comprises at least one of a recommendation filter responsive to an adaptive recommendation profile, and a consultation filter responsive to an adaptive consultation profile, each of the adaptive recommendation profile and the adaptive consultation profile being at least partially responsive to the feedback profile and the adaptive credibility profile.

83. The apparatus of claim 55 wherein:

a. the first processor further includes means for creating a plurality of mode-invariant concept components from the raw informons;

b. the second processor further includes means for concept-based indexing the plurality of mode-

invariant concept components into a collection of indexed informons; and

c. the second processor further includes means for creating the community profile from the collection of indexed informons.

84. The apparatus of claim 83 wherein the second processor further comprises an interactive distributed plurality of mindpool managers having tiers between the data stream and a plurality of users, the distributed plurality successively extracting selected informons responsive to a respective tier profile, the tier profile being closest to the plurality of users being the respective member client profile, the distributed plurality extracting the proposed informon from the data stream for each respective user thereby.

ABSTRACT

An apparatus, method, and computer program product for information filtering in a computer system receiving a data stream from a computer network, the data stream having raw informons embedded therein, at least one of the raw informons being of interest to a user, the user being a member client of a community. The method includes the steps of providing a dynamic informon characterization having profiles encoded therein, including an adaptive content profile and an adaptive collaboration profile; adaptively filtering the raw informons responsive to the dynamic informon characterization, and producing a proposed informon; presenting the proposed informon to the user; receiving a feedback profile from the user, responsive to the proposed informon; adapting the adaptive content profile, the adaptive collaboration profile, or both responsive to the feedback profile; and updating the dynamic informon characterization responsive to the previous adapting step. The apparatus includes a plurality of processors for providing interactive, distributed filtering of information, extracted from a computer network data stream in response to multiple attribute profiles.

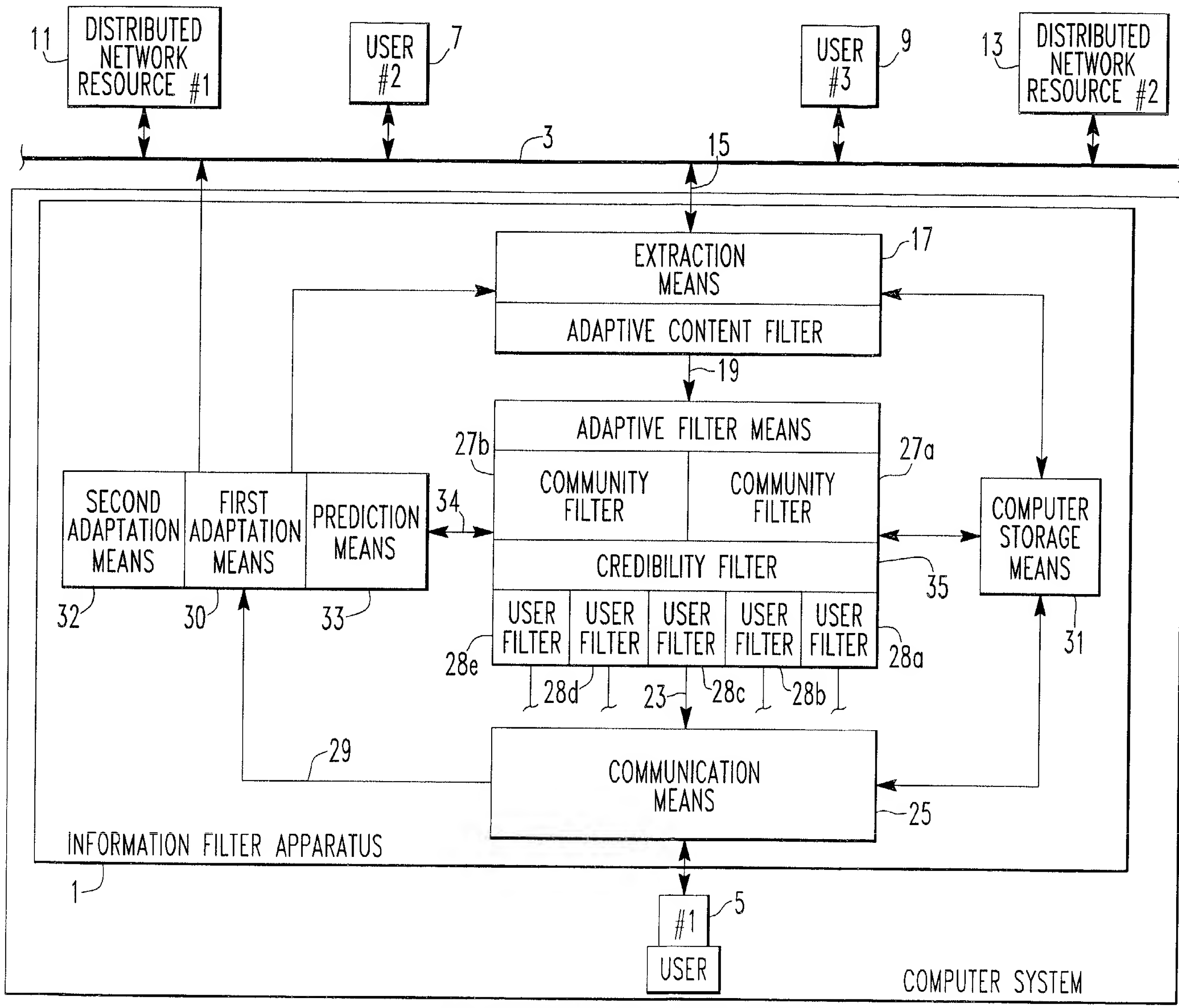
DISTRIBUTED NETWORK RESOURCE #1
11
USER #2
7
USER #3
9
DISTRIBUTED NETWORK RESOURCE #2
13
3
15
EXTRACTION MEANS
ADAPTIVE CONTENT FILTER
17
19
ADAPTIVE FILTER MEANS
COMMUNITY FILTER
COMMUNITY FILTER
27b
27a
CREDIBILITY FILTER
USER FILTER
USER FILTER
USER FILTER
USER FILTER
USER FILTER
28e
28d
23
28c
28b
28a
35
34
SECOND ADAPTATION MEANS
FIRST ADAPTATION MEANS
PREDICTION MEANS
32
30
33
COMPUTER STORAGE MEANS
31
29
COMMUNICATION MEANS
25
INFORMATION FILTER APPARATUS
1
#1
USER
5
COMPUTER SYSTEM
16

FIG. 1

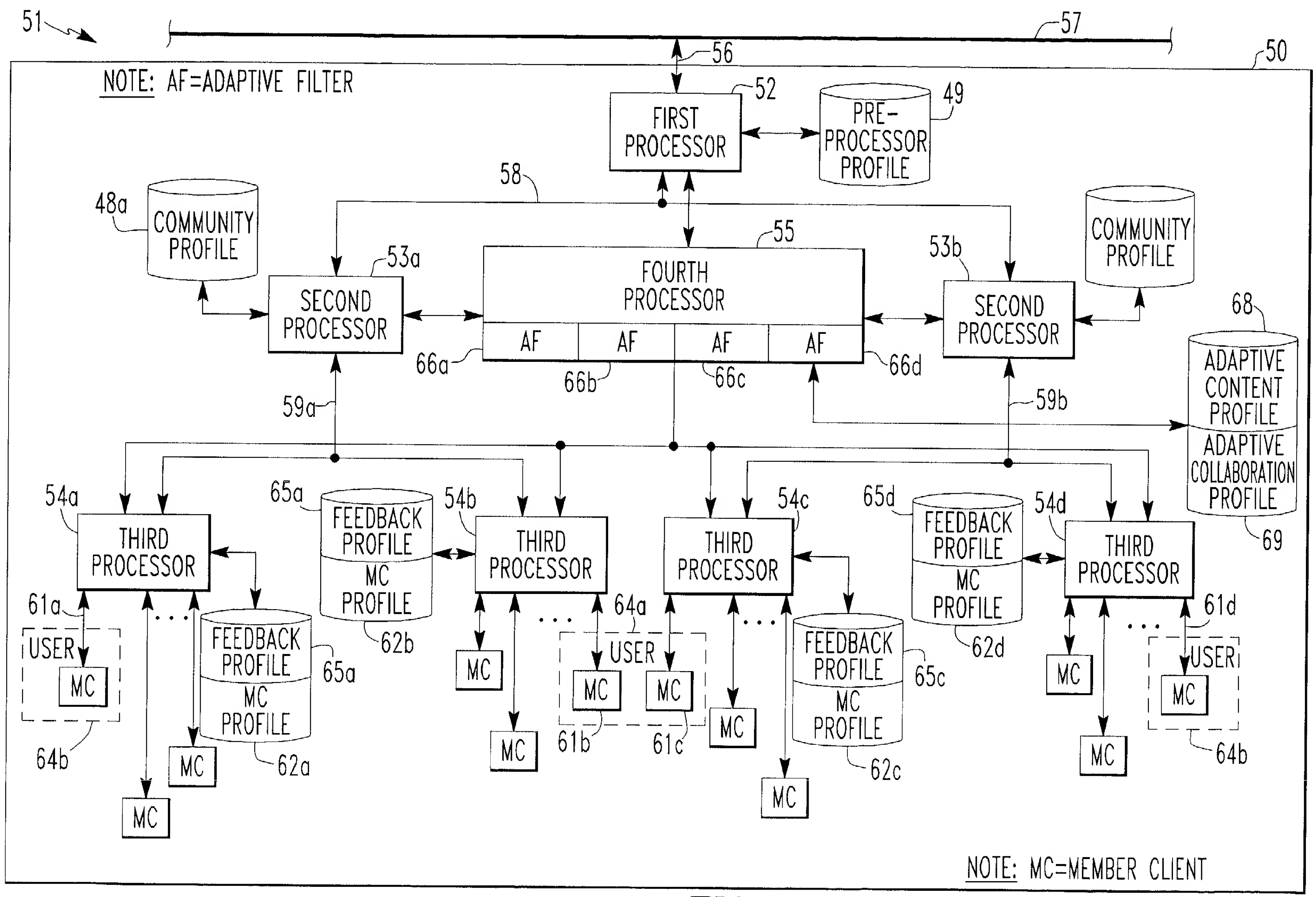

FIG. 2

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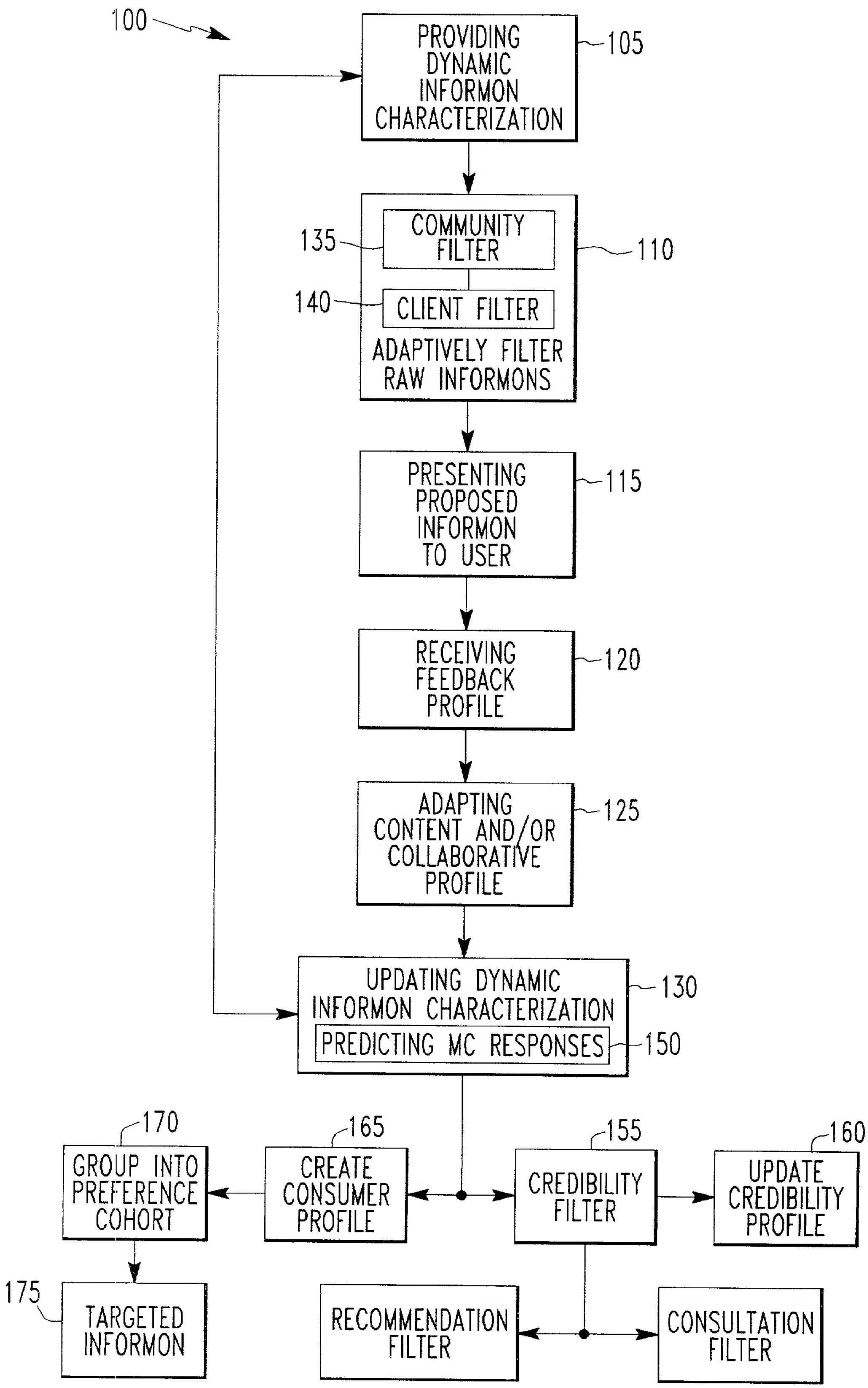
100
PROVIDING DYNAMIC INFORMON CHARACTERIZATION
105
COMMUNITY FILTER
135
CLIENT FILTER
140
ADAPTIVELY FILTER RAW INFORMONS
110
PRESENTING PROPOSED INFORMON TO USER
115
RECEIVING FEEDBACK PROFILE
120
ADAPTING CONTENT AND/OR COLLABORATIVE PROFILE
125
UPDATING DYNAMIC INFORMON CHARACTERIZATION
130
PREDICTING MC RESPONSES
150
GROUP INTO PREFERENCE COHORT
170
CREATE CONSUMER PROFILE
165
CREDIBILITY FILTER
155
UPDATE CREDIBILITY PROFILE
160
TARGETED INFORMON
175
RECOMMENDATION FILTER
CONSULTATION FILTER

FIG. 3

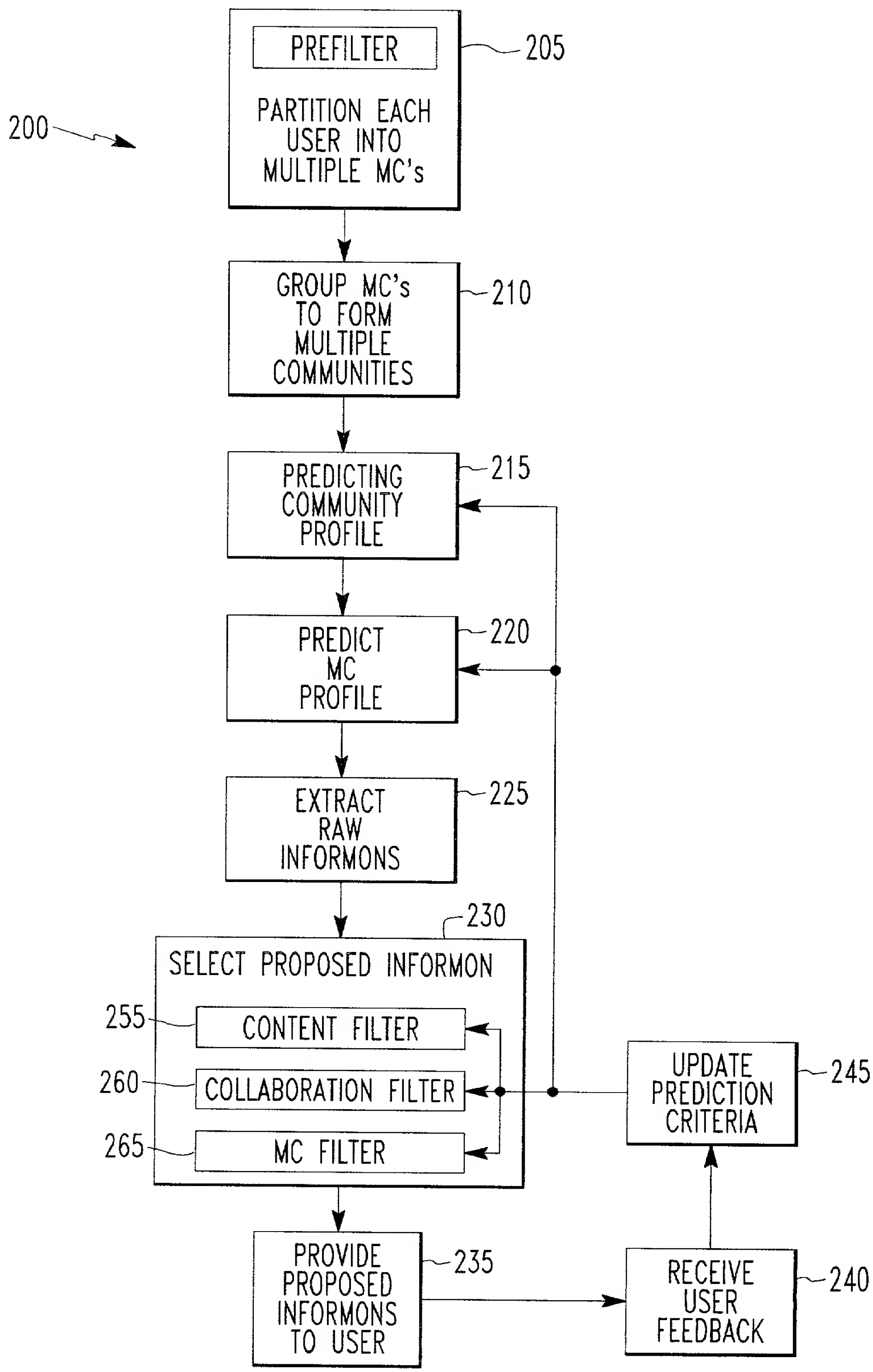
200
PREFILTER
PARTITION EACH USER INTO MULTIPLE MC's
205
GROUP MC's TO FORM MULTIPLE COMMUNITIES
210
PREDICTING COMMUNITY PROFILE
215
PREDICT MC PROFILE
220
EXTRACT RAW INFORMONS
225
SELECT PROPOSED INFORMON
230
CONTENT FILTER
255
COLLABORATION FILTER
260
MC FILTER
265
PROVIDE PROPOSED INFORMONS TO USER
235
RECEIVE USER FEEDBACK
240
UPDATE PREDICTION CRITERIA
245

FIG. 4

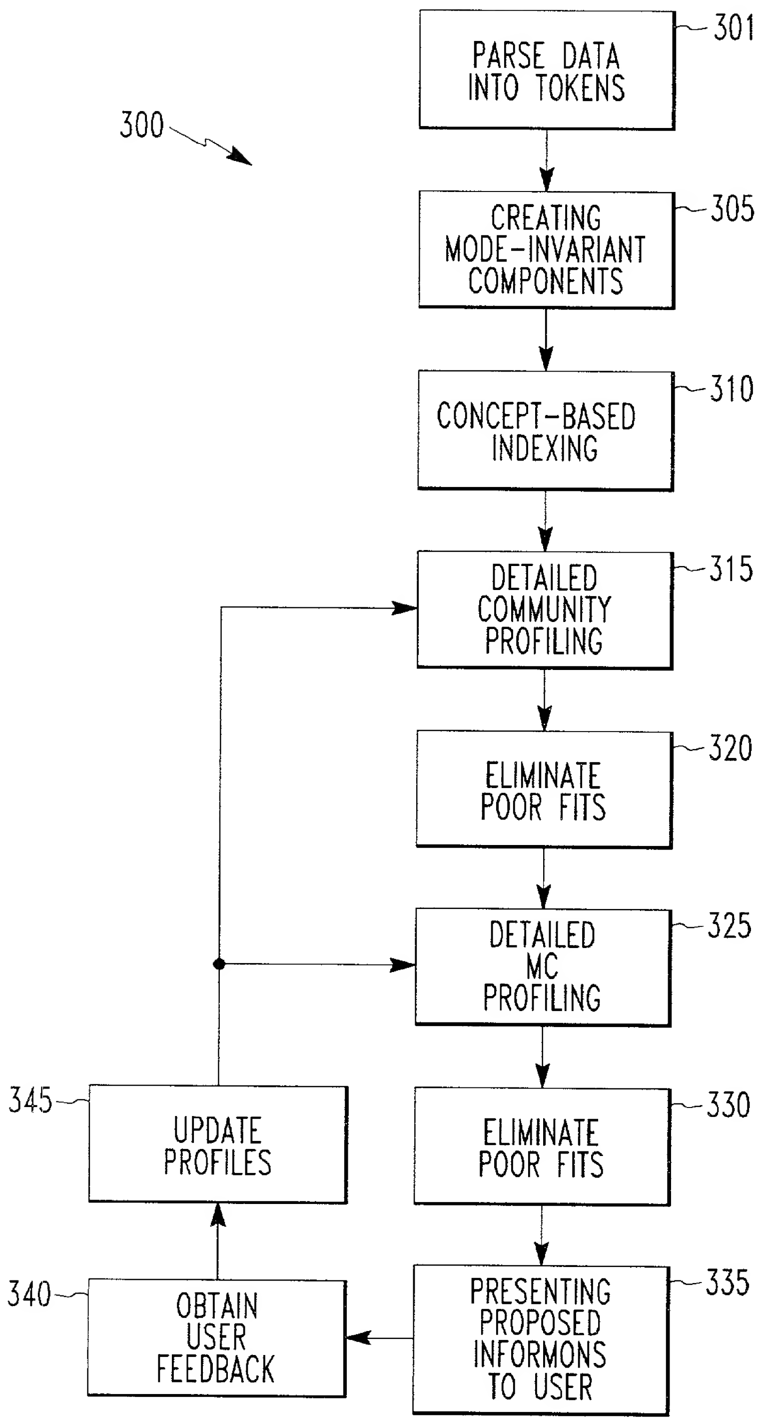
300
PARSE DATA INTO TOKENS
301
CREATING MODE-INVARIANT COMPONENTS
305
CONCEPT-BASED INDEXING
310
DETAILED COMMUNITY PROFILING
315
ELIMINATE POOR FITS
320
DETAILED MC PROFILING
325
ELIMINATE POOR FITS
330
PRESENTING PROPOSED INFORMONS TO USER
335
OBTAIN USER FEEDBACK
340
UPDATE PROFILES
345

FIG. 5

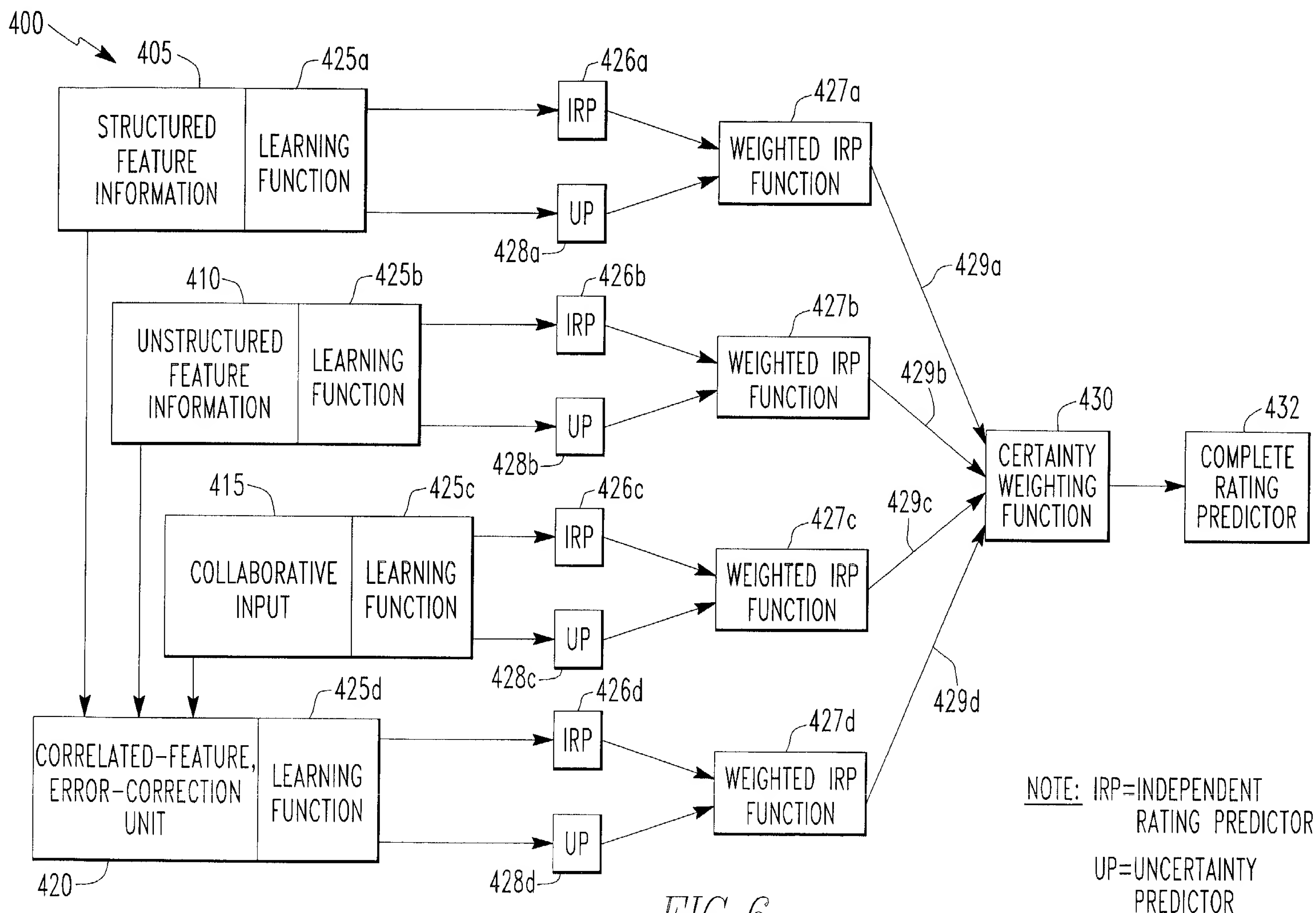
400
405
STRUCTURED FEATURE INFORMATION
LEARNING FUNCTION
425a
410
UNSTRUCTURED FEATURE INFORMATION
LEARNING FUNCTION
425b
415
COLLABORATIVE INPUT
LEARNING FUNCTION
425c
CORRELATED-FEATURE, ERROR-CORRECTION UNIT
LEARNING FUNCTION
425d
420
IRP
426a
UP
428a
IRP
426b
UP
428b
IRP
426c
UP
428c
IRP
426d
UP
428d
WEIGHTED IRP FUNCTION
427a
WEIGHTED IRP FUNCTION
427b
WEIGHTED IRP FUNCTION
427c
WEIGHTED IRP FUNCTION
427d
429a
429b
429c
429d
CERTAINTY WEIGHTING FUNCTION
430
COMPLETE RATING PREDICTOR
432
NOTE: IRP=INDEPENDENT RATING PREDICTOR
UP=UNCERTAINTY PREDICTOR

FIG. 6

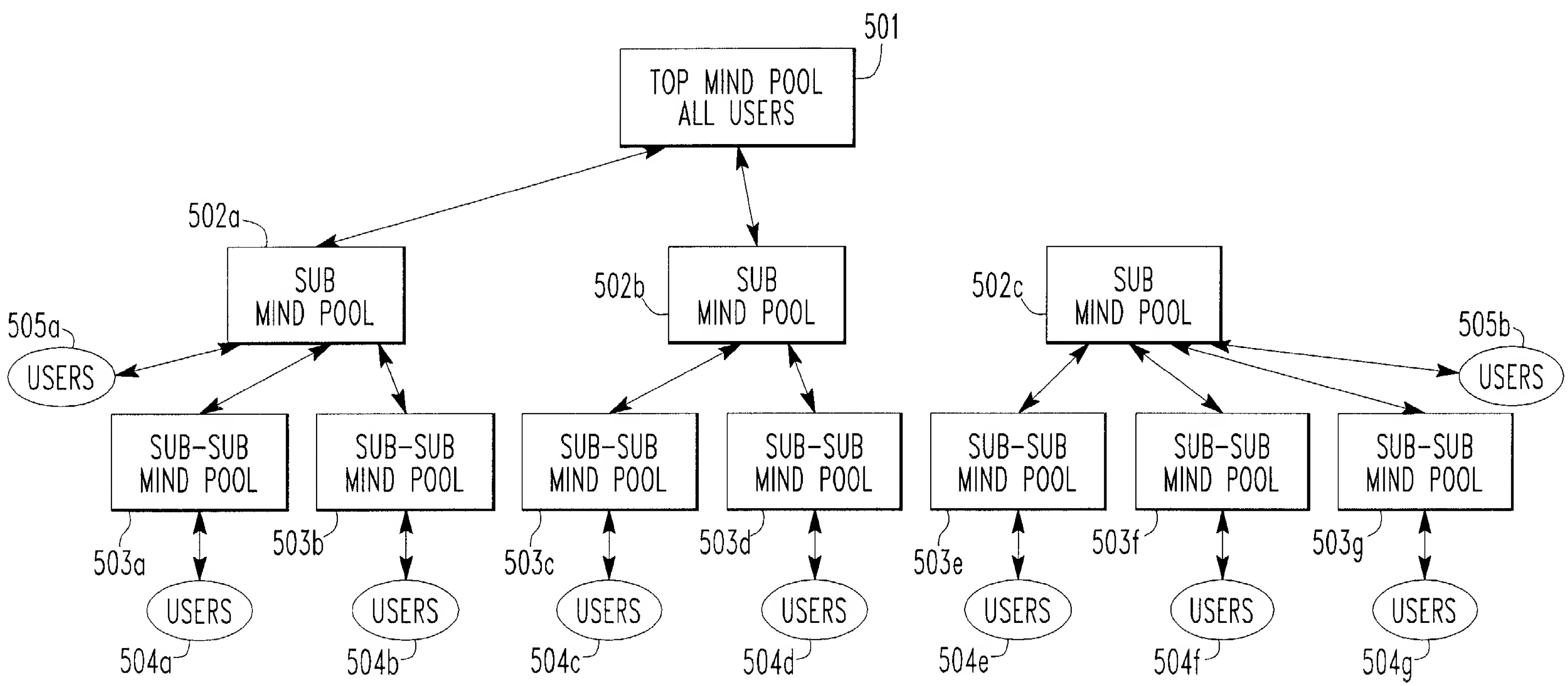
501
TOP MIND POOL ALL USERS
502a
SUB MIND POOL
502b
SUB MIND POOL
502c
SUB MIND POOL
505a
USERS
505b
USERS
SUB-SUB MIND POOL
503a
SUB-SUB MIND POOL
503b
SUB-SUB MIND POOL
503c
SUB-SUB MIND POOL
503d
SUB-SUB MIND POOL
503e
SUB-SUB MIND POOL
503f
SUB-SUB MIND POOL
503g
USERS
504a
USERS
504b
USERS
504c
USERS
504d
USERS
504e
USERS
504f
USERS
504g

FIG. 7

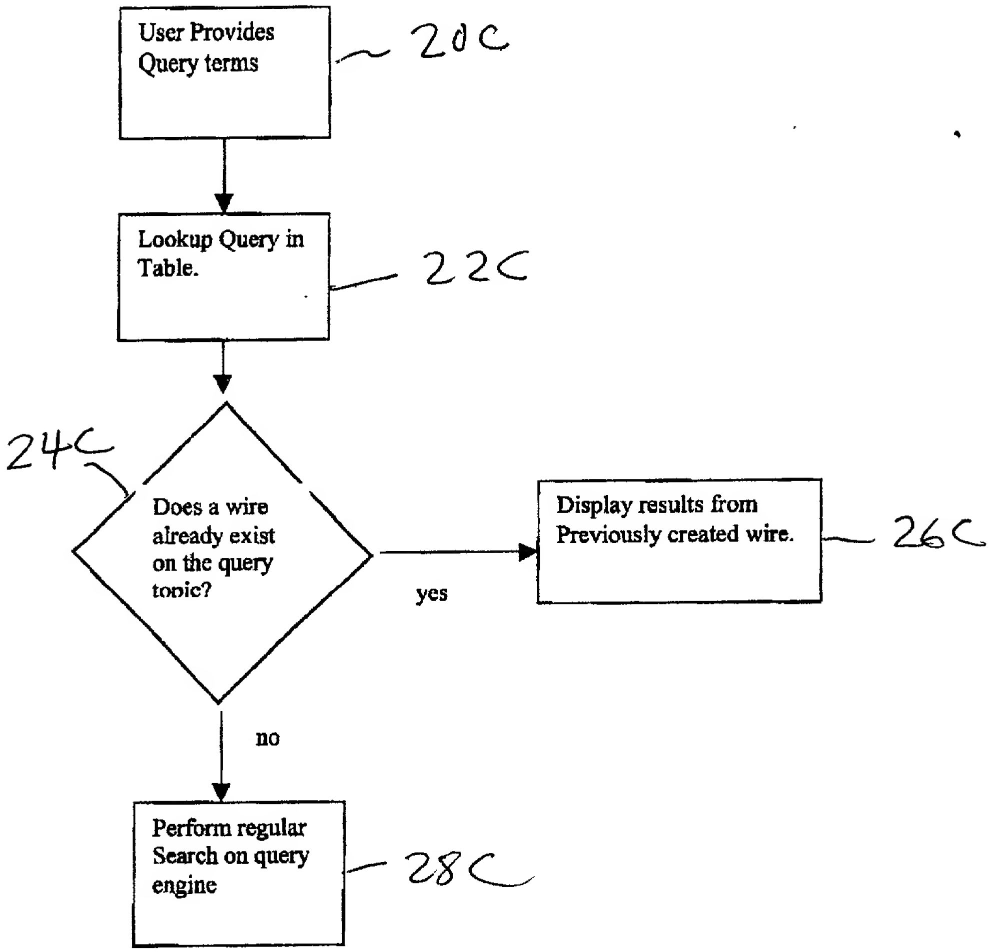
User Provides Query terms
20C
Lookup Query in Table.
22C
24C
Does a wire already exist on the query topic?
yes
Display results from Previously created wire.
26C
no
Perform regular Search on query engine
28C

Figure 8

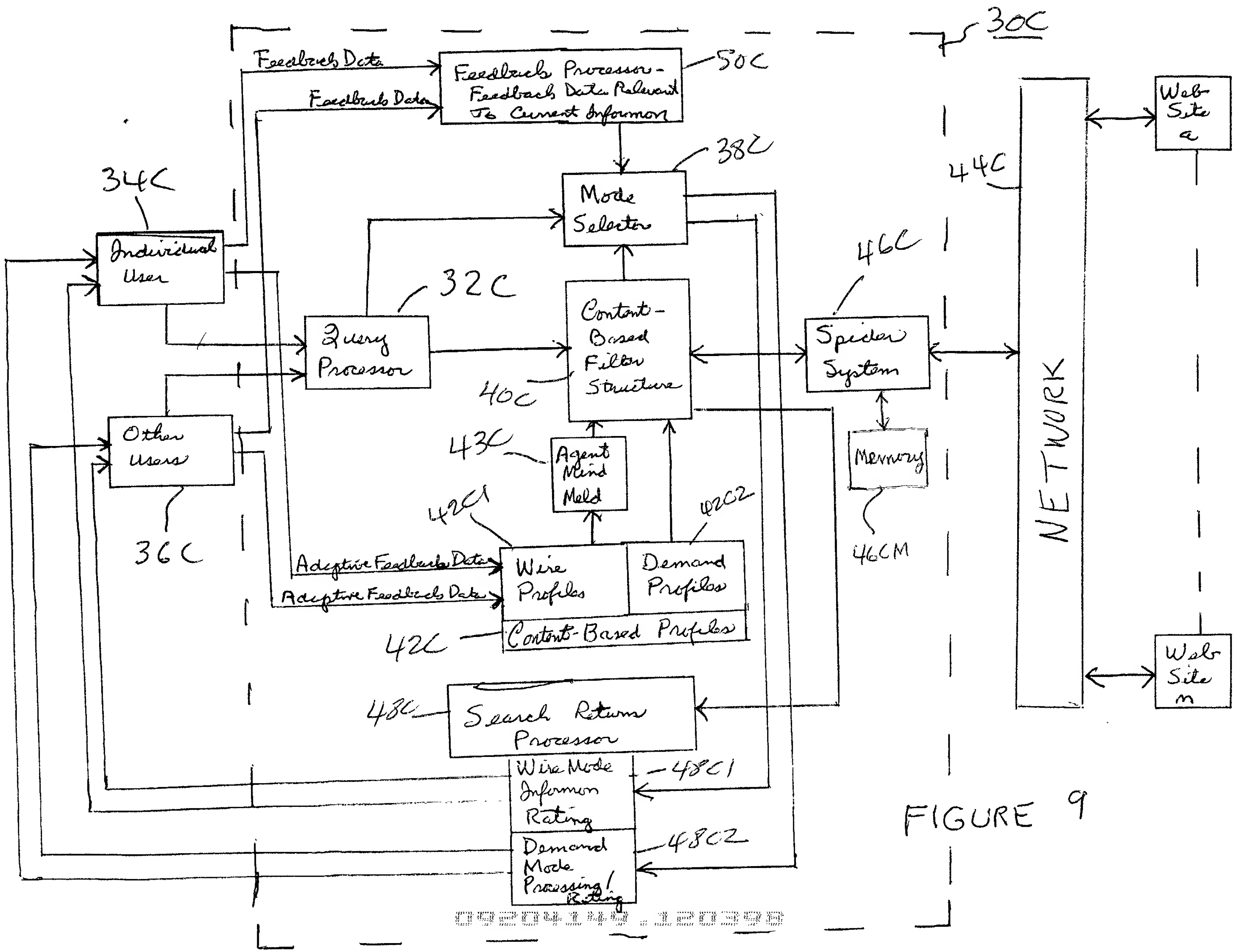

FIGURE 9

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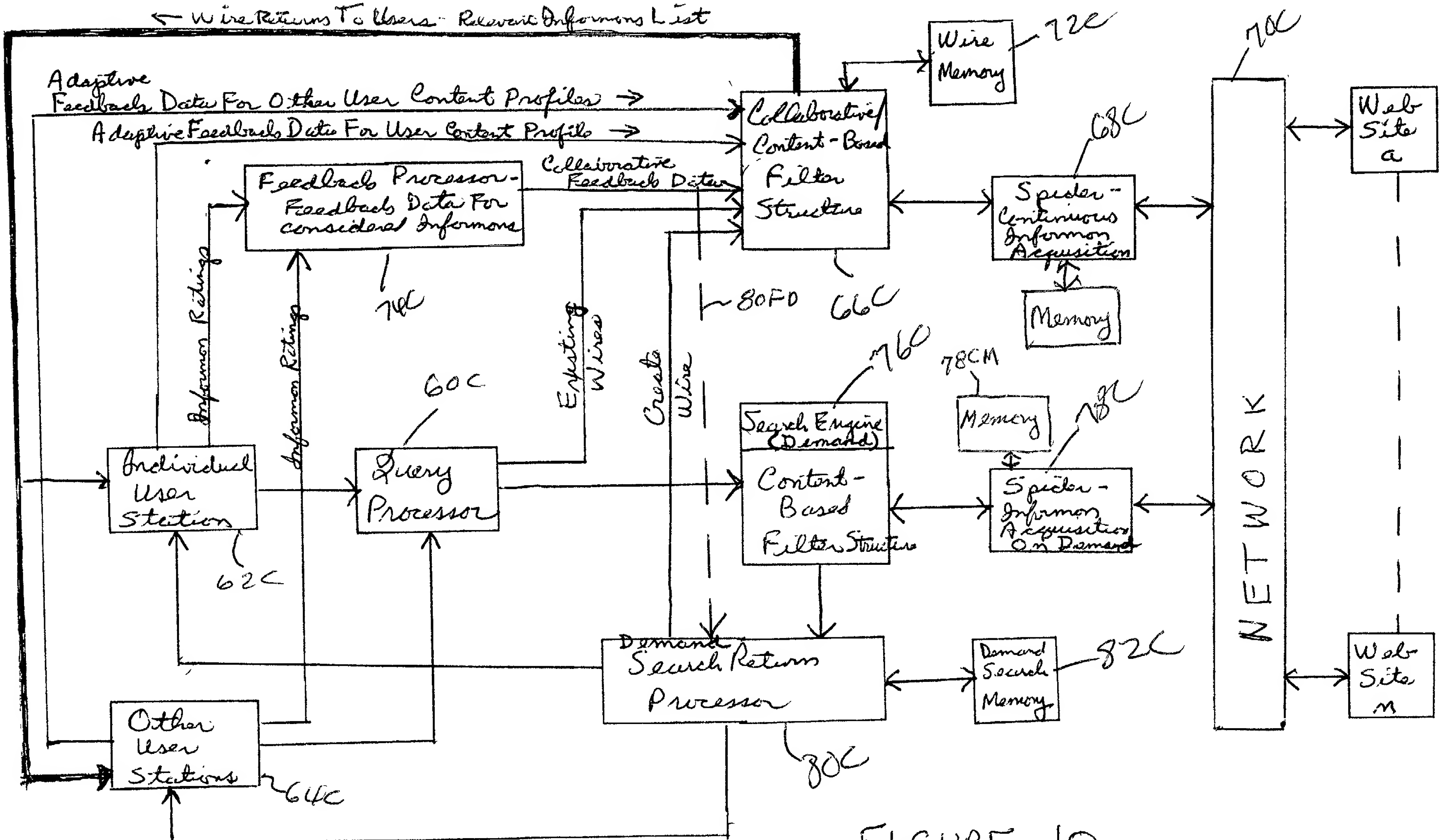

FIGURE 10

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LYC5

PTO/SB/01 (6-95)
Approved for use through 06/30/98. OMB 0651-0032
Patent and Trademark Office: U.S. DEPARTMENT OF COMMERCE

DECLARATION FOR PATENT APPLICATION

Docket Number (Optional)
D2306-00002

As a below named inventor, I hereby declare that:

My residence, post office address and citizenship are as stated below next to my name.

I believe I am the original, first and sole inventor (if only one name is listed below) or an original, first and joint inventor (if plural names are listed below) of the subject matter which is claimed and for which a patent is sought on the invention entitled An Information Filter In A Computer System And A Method Therefor, the specification of which is attached hereto unless the following box is checked:

☐ was filed on ____________ as United States Application Number or PCT International Application Number ____________ and was amended on ____________ (if applicable).

I hereby state that I have reviewed and understand the contents of the above identified specification, including the claims, as amended by any amendment referred to above.

I acknowledge the duty to disclose information which is material to patentability as defined in 37 CFR § 1.56.

I hereby claim foreign priority benefits under 35 U.S.C. § 119(a)-(d) or § 365(b) of any foreign application(s) for patent or inventor's certificate, or § 365(a) of any PCT International application which designated at least one country other than the United States, listed below and have also identified below, by checking the box, any foreign application for patent or inventor's certificate, or PCT International application having a filing date before that of the application on which priority is claimed.

Prior Foreign Application(s) — Priority Not Claimed

(Number)	(Country)	(Day/Month/Year Filed)	Priority Not Claimed
			☐
			☐

I hereby claim the benefit under 35 U.S.C. § 119(e) of any United States provisional application(s) listed below.

(Application Number)	(Filing Date)

I hereby claim the benefit under 35 U.S.C. § 120 of any United States application(s), or § 365(c) of any PCT International application designating the United States, listed below and, insofar as the subject matter of each of the claims of this application is not disclosed in the prior United States or PCT International application in the manner provided by the first paragraph of 35 U.S.C. § 112, I acknowledge the duty to disclose information which is material to patentability as defined in 37 CFR § 1.56 which became available between the filing date of the prior application and the national or PCT International filing date of this application.

(Application Number)	(Filing Date)	(Status -- patented, pending, abandoned)

I hereby appoint the following attorney(s) and/or agent(s) to prosecute this application and to transact all business in the Patent and Trademark Office connected therewith:

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One Liberty Place
Philadelphia, PA 19103-7396

I hereby declare that all statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and that such willful false statements may jeopardize the validity of the application or any patent issued thereon.

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Inventor's signature Andrew K. Lang Date 4/4/96
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Second Inventor's signature Donald M. Kosak Date 4/4/96
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☐ Additional inventors are being named on separately numbered sheets attached hereto.